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Nondeterministic Approaches and Their Potential for Future Aerospace Systems

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Preface

This document contains the proceedings of the Training Workshop on Nondeterministic Approaches and their Potential for Future Aerospace Systems held at NASA Langley Research Center, Hampton, Virginia, May 30-31, 2001. The workshop was jointly sponsored by Old Dominion University and NASA. Workshop attendees came from NASA, other government agencies, industry, and universities. The objectives of the workshop were to review the diverse activities in nondeterministic approaches, uncertainty management methodologies, reliability assessment and risk management techniques, and to identify their potential for future aerospace systems.

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Perspectives on Nondeterministic Approaches

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INTRODUCTION

Increasingly more complex systems are being built and conceived by high-tech industries. Engineers are asked to design faster, and to insert new technologies into these systems. Increasing reliance is being made on modeling, simulation and virtual prototyping to find globally optimal designs that take uncertainties and risk into consideration. Conventional computational and design methods are inadequate to handle these tasks. Therefore, intense effort has been devoted in recent years to nontraditional methods for solving complex problems with system uncertainties.

An attempt is made in this overview to give broad definitions to the terms and to set the stage for the succeeding presentations. The presentation is divided into four parts (see Figure 1). In the first part, examples of future aerospace systems are given, along with some of their major characteristics and design drivers. The second part describes the synergistic coupling of the key technologies that can significantly enhance the modeling and simulation technologies. The third part describes the future research and learning environments required for the realization of the full potential of nondeterministic approaches. The fourth part lists the objectives of the workshop and some of the sources of information on nondeterministic approaches.

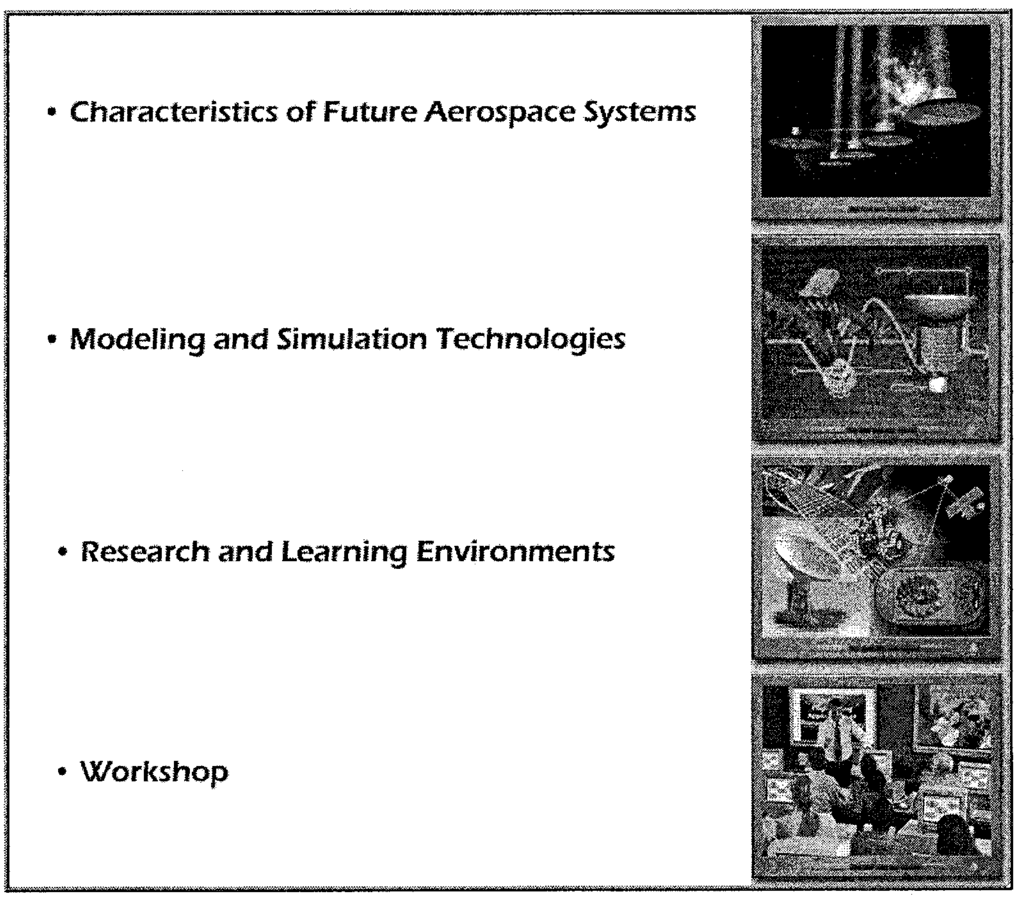

Figure 1

EXAMPLES OF FUTURE AEROSPACE SYSTEMS AND SOME OF THEIR CHARACTERISTICS

The realization of NASA's ambitious goals in aeronautics and space with the current national budget constraints will require new kinds of aerospace systems and missions that use novel technologies and manage risk in new ways. Future aerospace systems must be autonomous, evolvable, resilient, and highly distributed. Two examples are given in Figure 2. The first is a biologically inspired aircraft with self-healing wings that flex and react like living organisms. It is built of a multifunctional material with fully integrated sensing and actuation, and unprecedented levels of aerodynamic efficiencies and aircraft control. The second is an integrated human-robotic outpost, with biologically inspired robots. The robots could enhance the astronaut's capabilities to do large-scale mapping, detailed exploration of regions of interest, and automated sampling of rocks and soil. They could enhance the safety of the astronauts by alerting them to mistakes before they are made, and letting them know when they are showing signs of fatigue, even if they are not aware of it.

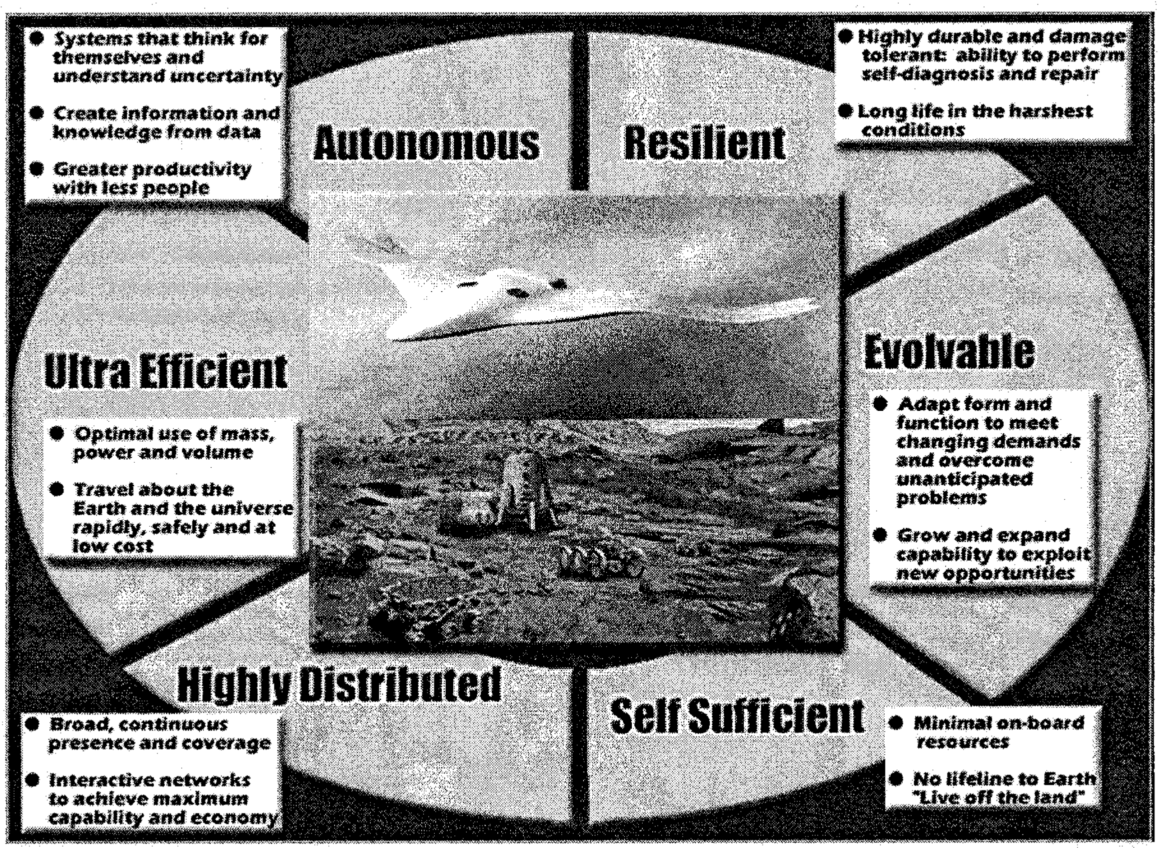

Figure 2

DEFINITIONS OF UNCERTAINTY AND A BRIEF HISTORICAL ACCOUNT OF UNCERTAINTY MODELING

Uncertainty is an acknowledged phenomenon in the natural and technological worlds. Engineers are continually faced with uncertainties in their designs. However, there is no unique definition of uncertainty. A useful functional definition of uncertainty is: the information/knowledge gap between what is known and what needs to be known for optimal decisions, with minimal risk.

Prior to the twentieth century, uncertainty and other types of imprecisions were considered to be unscientific, and therefore, not addressed. It was not until the beginning of the twentieth century that statistical mechanics emerged and was accepted as a legitimate area of science. It was taken for granted that uncertainty is adequately captured by probability theory. It took sixty years to recognize that the conceptual uncertainty is too deep to be captured by probability theory alone and to initiate studies of non-probabilistic manifestations of uncertainty, as well as their applications in engineering and science. In the last two decades, significant advances have been made in uncertainty modeling, the level of sophistication has increased, and a number of software systems have been developed. Among the recent developments are the perception-based information processing and methodology of computing with words (Figure 3).

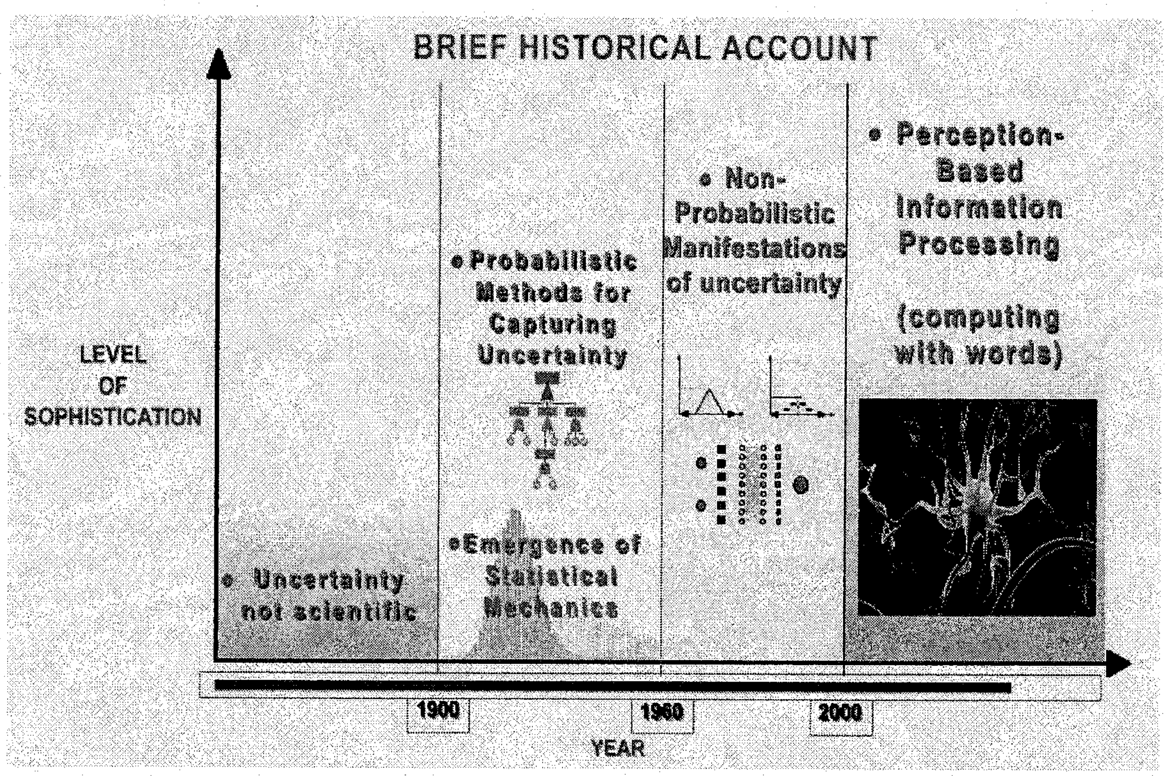

Figure 3

TYPES OF UNCERTAINTIES

A number of different uncertainty representations and classifications have been proposed. Among these classifications are the three-type classification – statistical, model, and fundamental uncertainties; the two type classification – uncertainty of information and uncertainty of the reasoning process; and the six-type classification (see Figure 4):

- *Probabilistic uncertainty*, which arises due to chance or randomness,
- *Fuzzy uncertainty* due to linguistic imprecision (e.g., set boundaries are not sharply defined),
- *Model uncertainty* which is attributed to lack of information about the model characteristics,
- *Uncertainty due to limited (fragmentary) information* available about the system (for example, in the early stage of the design process),
- *Resolutional uncertainty* which is attributed to limitation of resolution (e.g., sensor resolution), and
- *Ambiguity* (i.e., one to many relations).

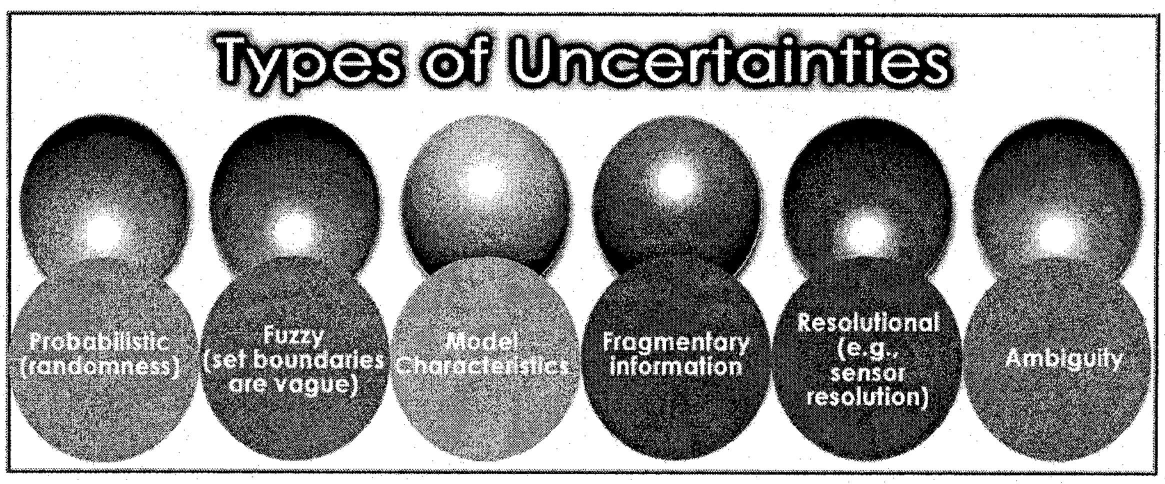

Figure 4

MANAGING UNCERTAINTIES

While completely eliminating uncertainty in engineering design is not possible, reducing and mitigating its effects have been the objectives of the emerging field of uncertainty management. The field draws from several disciplines including statistics, management science, organization theory, and inferential thinking (see Figure 5).

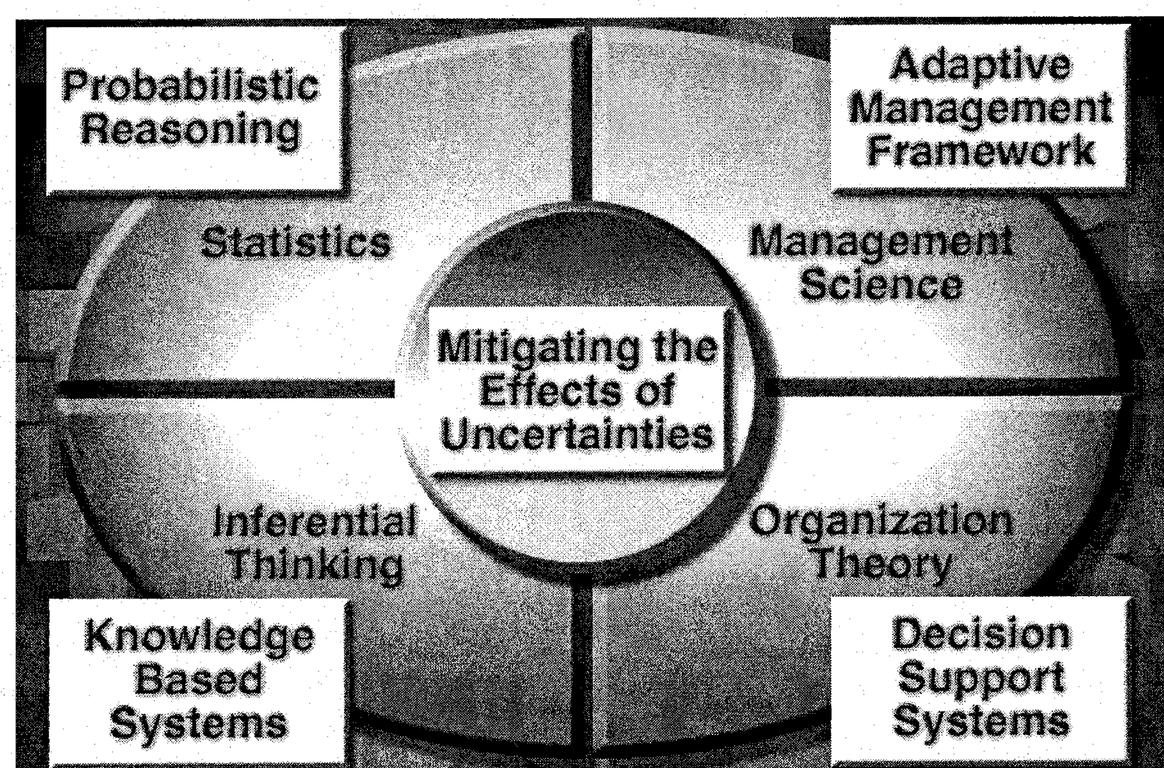

Figure 5

NONDETERMINISTIC ANALYSIS APPROACHES

Depending on the type of uncertainty and the amount of information available about the system characteristics and the operational environments, three categories of nondeterministic approaches can be identified for handling the uncertainties. The three approaches are (see Figure 6): probabilistic analysis, fuzzy-set approach, and set theoretical, convex (or anti-optimization) approach. In *probabilistic analysis*, the system characteristics and/or the source variables are assumed to be random variables (or functions), and the joint probability density functions of these variables are selected. The main objective of the analysis is the determination of the reliability of the system.

If the uncertainty is because of a vaguely defined system and/or operational characteristics, imprecision of data, and subjectivity of opinion or judgment, *fuzzy-set treatment* is appropriate. Randomness describes the uncertainty in the occurrence of an event (such as damage or failure).

When the information about the system and/or operational characteristics is fragmentary (e.g., only a bound on a maximum possible response function is known), then *convex modeling* is practical. Convex modeling produces the maximum or least-favorable response and the minimum or most favorable response of the system under the constraints within the set-theoretic description.

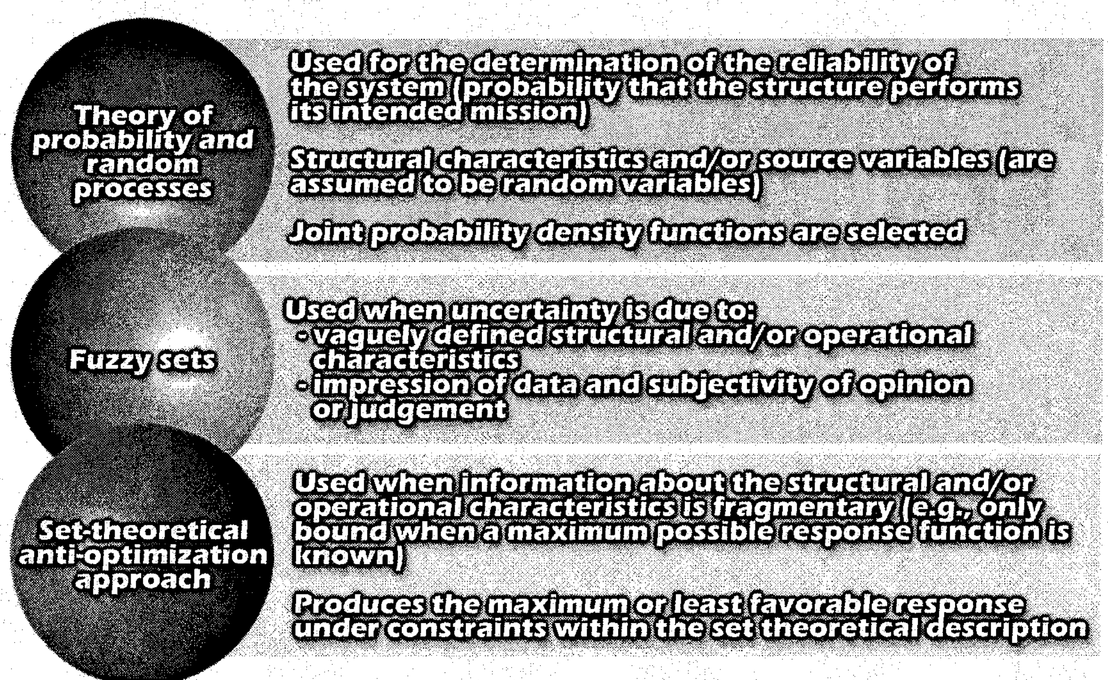

Figure 6

ENHANCING THE MODELING AND SIMULATION TECHNOLOGIES

The synergistic coupling of nondeterministic approaches with a number of key technologies can significantly enhance the modeling and simulation capabilities and meet the needs of future complex systems. The key technologies include: Virtual product development for simulating the entire lifecycle of the engineering system, reliability and risk management, intelligent software agents, knowledge and information, high performance computing, high capacity communications, human computer interfaces, and human performance.

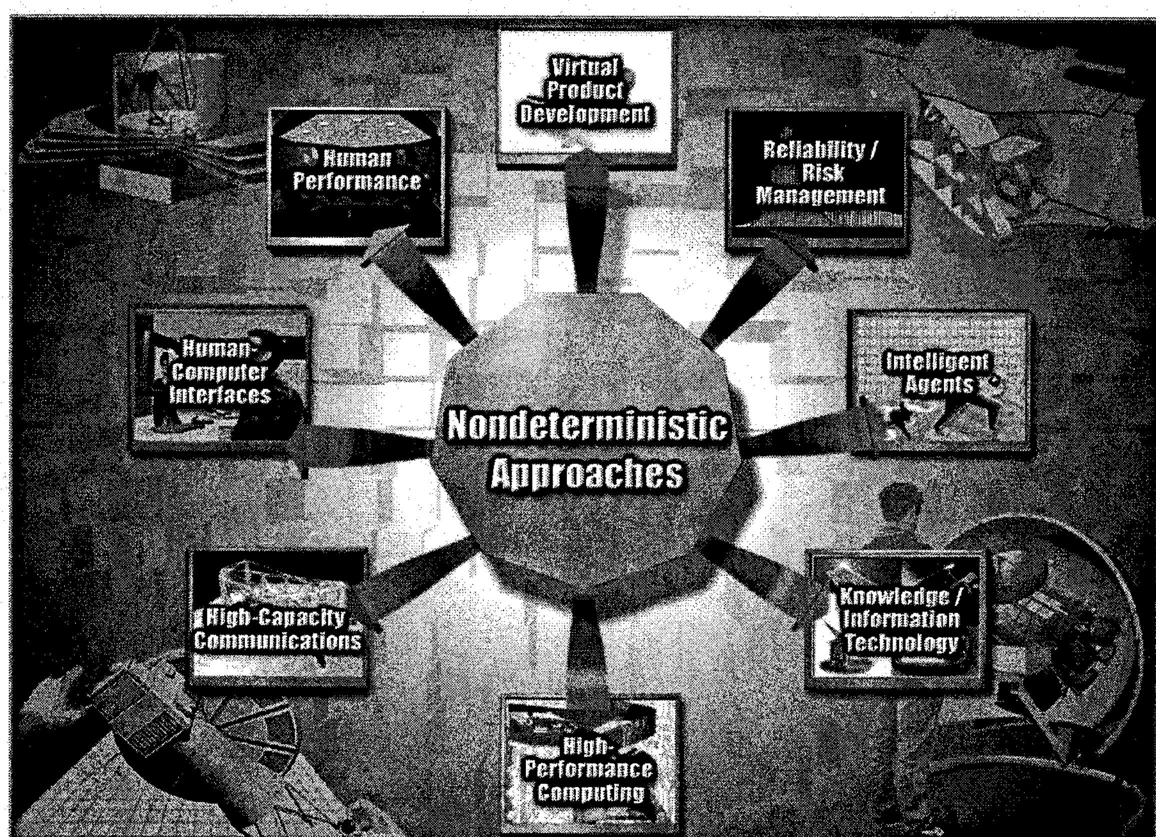

Figure 7

VIRTUAL PRODUCT DEVELOPMENT

Current virtual product development (VPD) systems have embedded simulation capabilities for the entire lifecycle of the product. As an example, the top-level system process flow for a space transportation system is shown in Figure 8. In each phase uncertainties are identified and appropriate measures are taken to mitigate their effects. Information Technology will change the product development from a sequence of distinct phases into a continuous process covering the entire lifecycle of the product with full interplay of information from beginning to end and everywhere throughout.

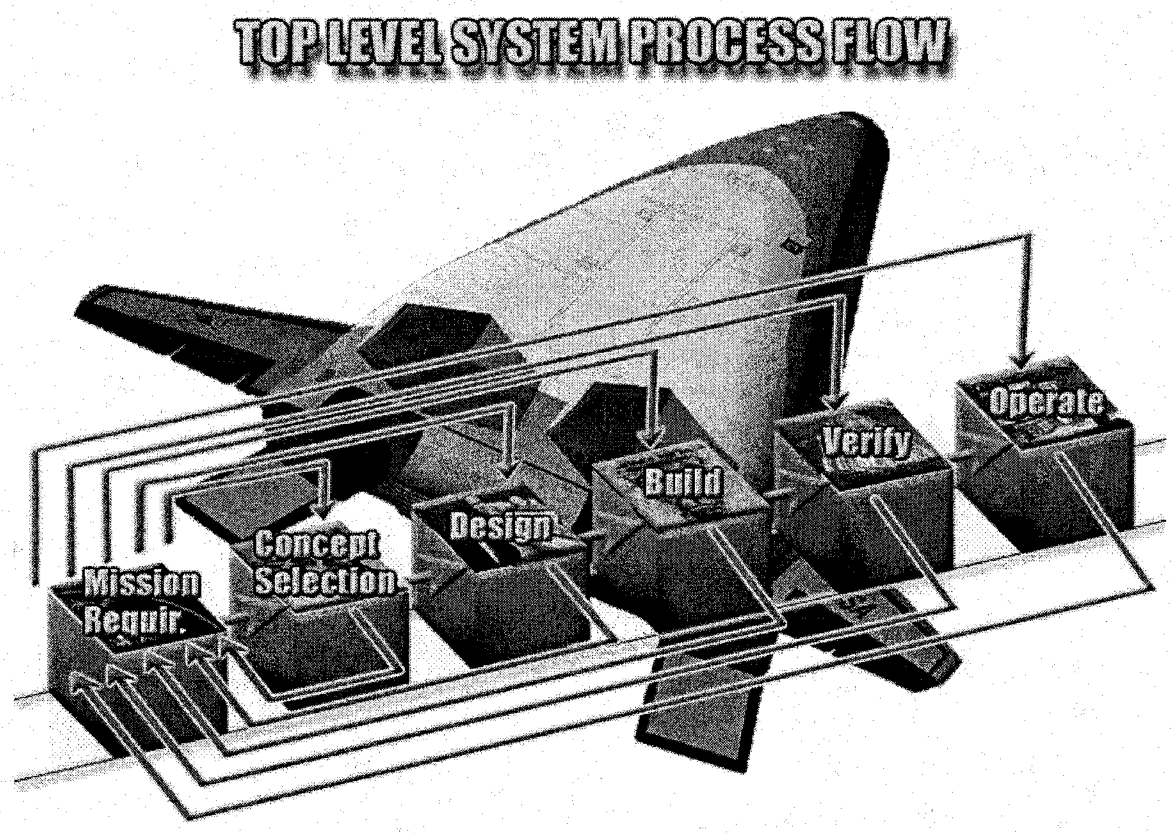

Figure 8

RELIABILITY ASSESSMENT

Reliability is defined as the probability that a component (or a system) will perform its intended function without failure for a specified period of time under designated operating conditions. Failure rate or hazard rate is an important function in reliability analysis since it provides a measure of the changes in the probability of failure over the lifetime of a component. In practice, it often exhibits a bathtub shape (see Figure 9).

Reliability assessment includes: selection of a reliability model, analysis of the model, calculation of the reliability performance indices, and evaluation of results, which includes establishment of confidence limits and decision on possible improvements.

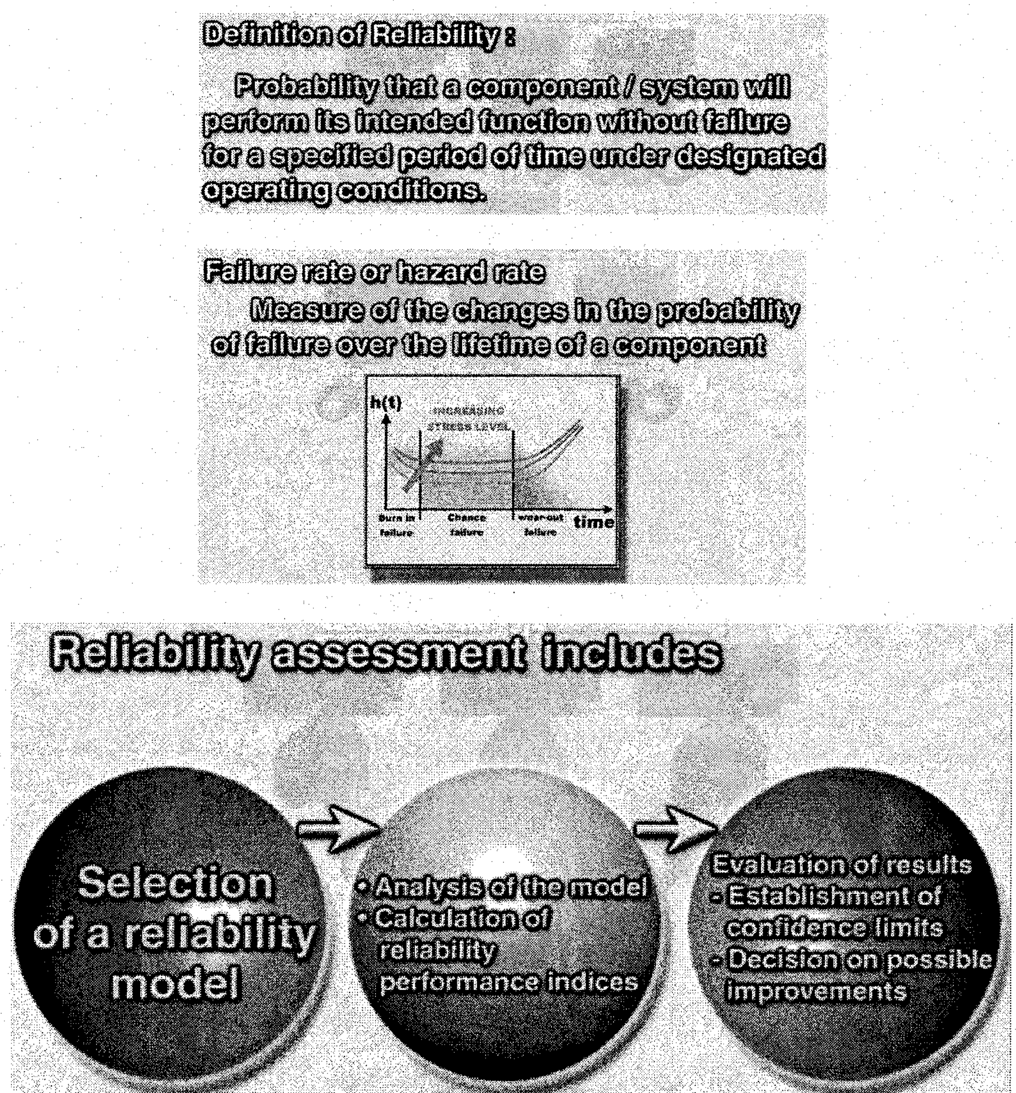

Figure 9

RISK MANAGEMENT PROCESS

Risk is defined as the uncertainty associated with a given design, coupled with its impact on performance, cost and schedule. Risk management is defined as the systems engineering and program management tools that can provide a means to identify and resolve potential problems.

The risk management process includes the following task (Figure 10):

- *Risk planning*: development of a strategy for identifying risk drivers.
- *Risk identification*: identifying risk associated with each technical process.
- *Risk analysis*: isolating the cause of each identified risk category and determining the effects.

The combination of risk identification and risk analysis is referred to as *risk assessment.*

- *Risk handling*: selecting and implementing options to set risk at acceptable levels.
- *Risk monitoring*: systematically tracking and evaluating the performance of risk handling actions.

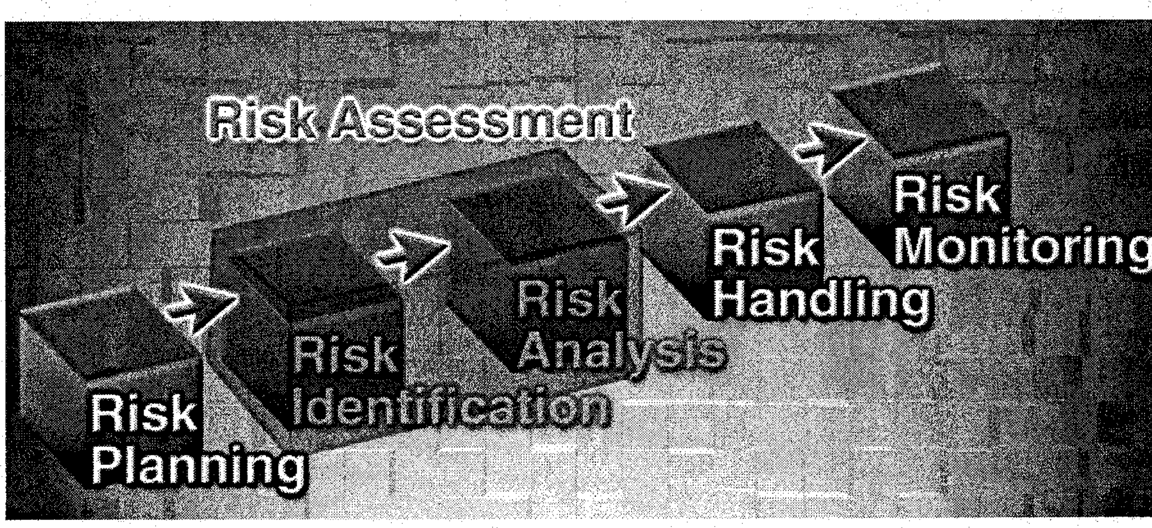

Figure 10

ROBUSTNESS

Robustness is defined as the degree of tolerance to variations (in either the components of a system or its environment). A robust ultra-fault-tolerant design of an engineering system is depicted in Figure 11. The performance of the system is relatively insensitive to variations in both the components and the environment. By contrast, a non-robust design is sensitive to variations in either or both.

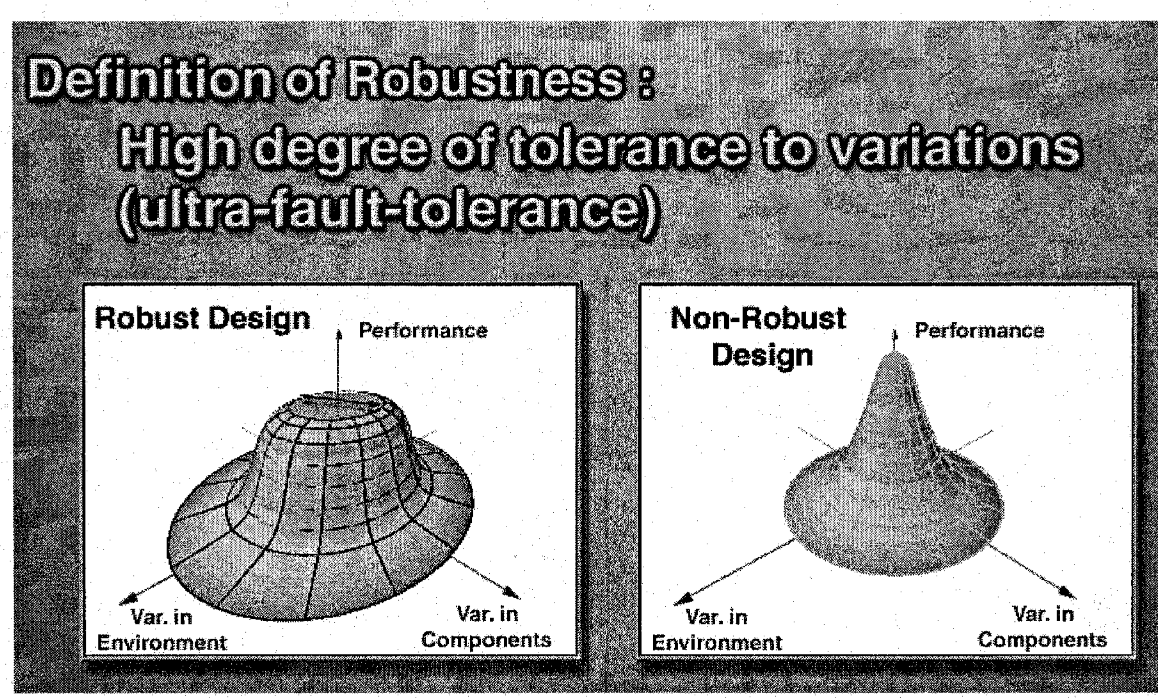

Figure 11

TERAMAC CONFIGURABLE CUSTOM COMPUTER

An example of a robust, ultra-fault-tolerant system is the Teramac Computer which is a one Tera Hertz massively parallel experimental computer built at Hewlett-Packard Laboratories to investigate a wide range of computational architectures (Figure 12). It contains 22,000 (3%) hardware defects, any one of which could prove fatal to a more conventional machine. It incorporates a high communication bandwidth that enables it to easily route around defects. It operates 100 times faster than a high-end single processor workstation (for some of its configurations).

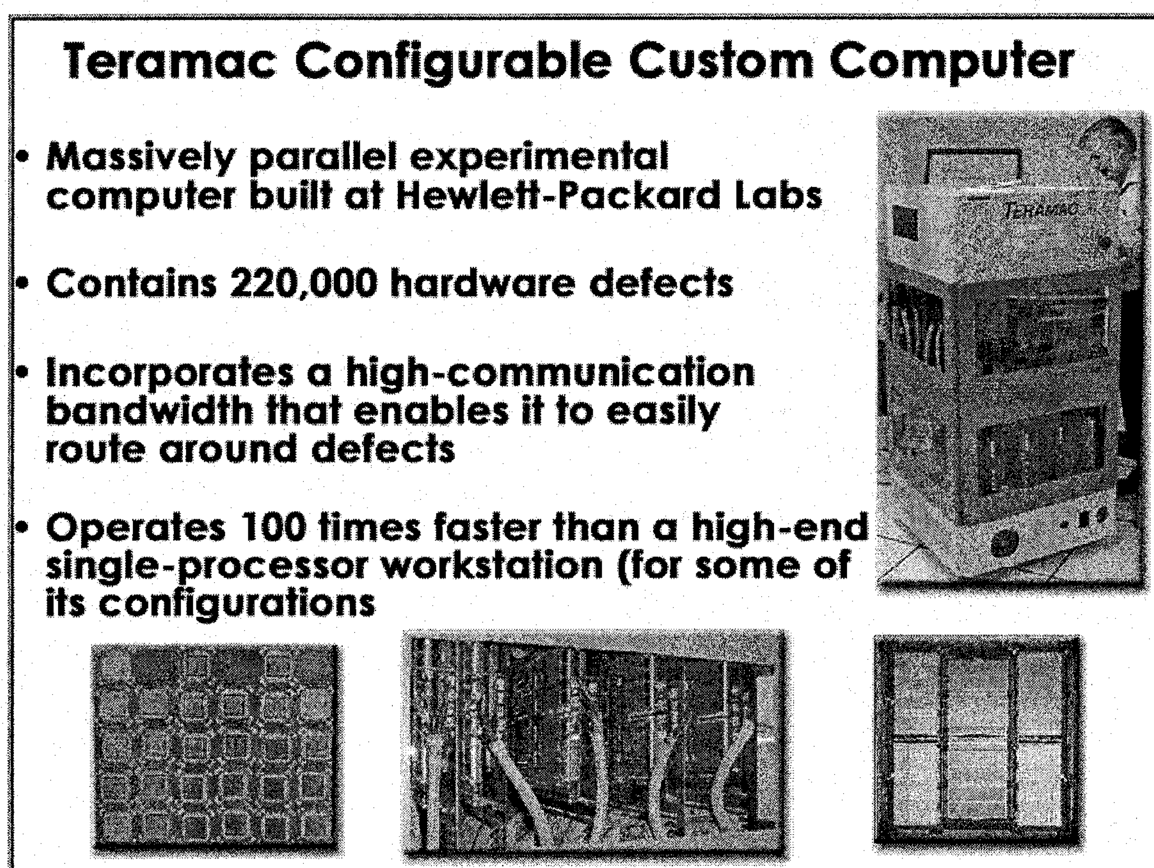

Figure 12

KEY COMPONENTS OF ADVANCED SIMULATION AND MODELING ENVIRONMENTS

The realization of the full potential of nondeterministic approaches in modeling and simulation requires an environment that links diverse teams of scientists, engineers, and technologists. The essential components of the environment can be grouped into three categories (Figure 13): intelligent tools and facilities, nontraditional methods, and advanced interfaces.

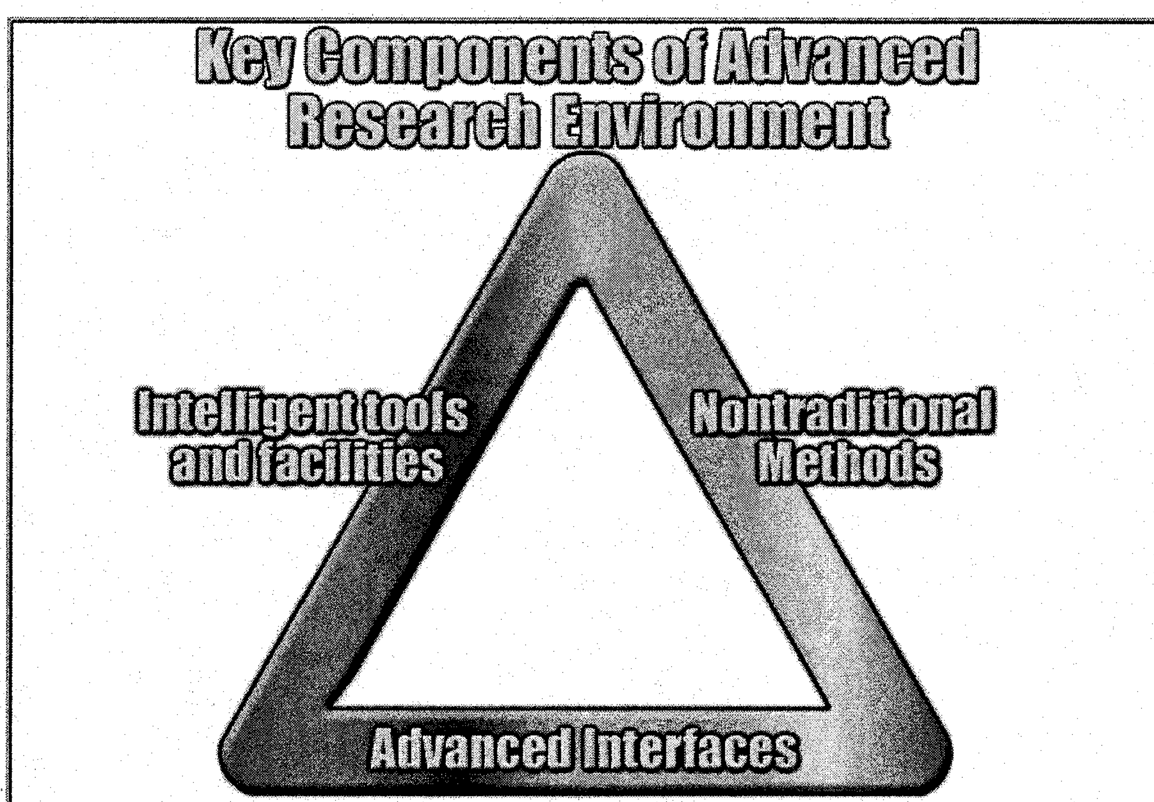

Figure 13

INTELLIGENT TOOLS AND FACILITIES

These include high fidelity – rapid modeling, lifecycle simulation and visualization tools, synthetic immersive environment; automatic and semiautomatic selection of software and hardware platforms; computer simulation of physical experiments and remote control of these experiments. In all of these tools, extensive use should be made of intelligent software agents and information technology (Figure 14).

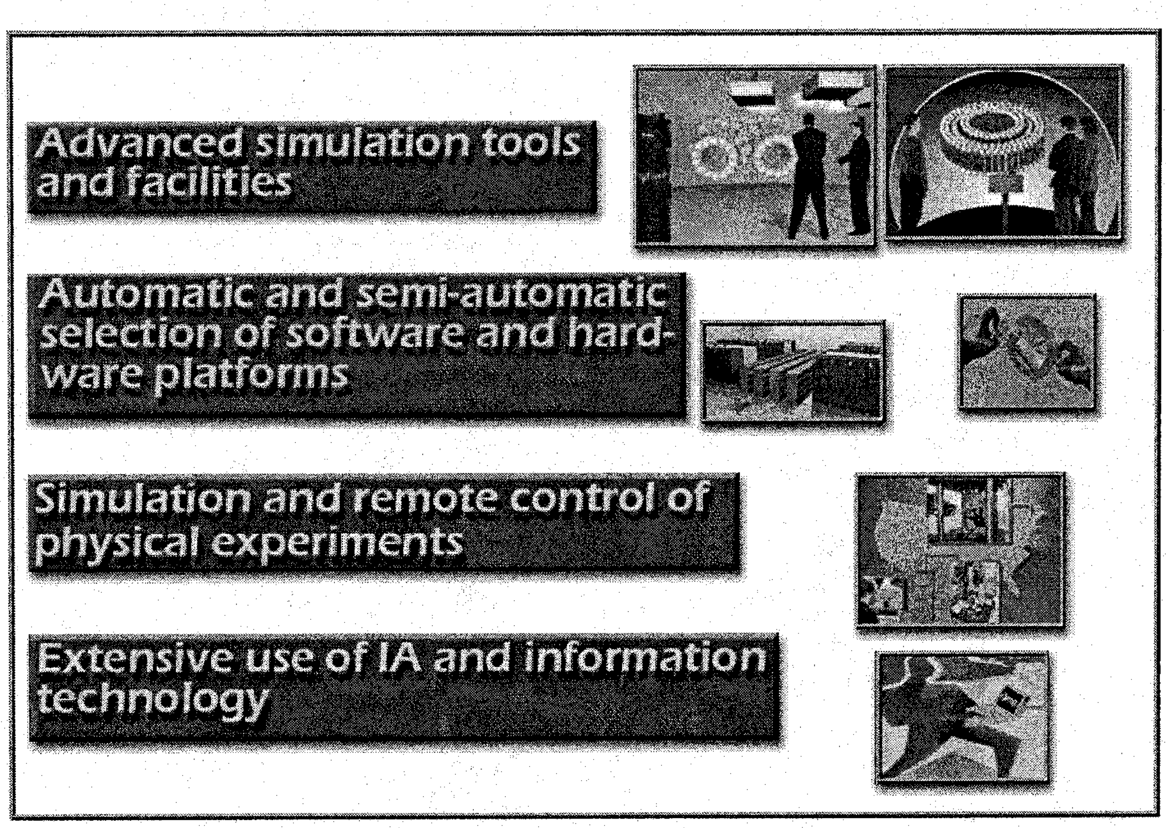

Figure 14

ADVANCED HUMAN/COMPUTER INTERFACES

Although the WIMP (windows, icons, menus, pointing devices) paradigm has provided a stable global interface, it will not scale to match the myriad from factors and uses of platforms in the future collaborative distributed environment. Perceptual user interfaces (PUI) are likely to meet those needs. PUI's integrate perceptive, multimodal and multimedia interfaces to bring human capabilities to bear on creating more natural intuitive interfaces. They enable multiple styles of interactions, such as speech only, speech and gesture, vision, and synthetic sound, each of which may be appropriate in different applications (Figure 15). These new technologies will enable broad uses of computers as assistants or agents that will interact in more human-like ways.

- **Integrates perceptive, multimodal and multimedia interfaces to bring human capabilities to bear on creating more natural and intuitive interfaces**
- **Enables multiple styles of interactions and broad uses of computers as assistants**

Figure 15

NONTRADITIONAL METHODS

These include multi-scale methods, strategies for highly coupled multi-physical problems, and nondeterministic approaches for handling uncertainty in geometry, material properties, boundary conditions, loading and operational environments (Figure 16).

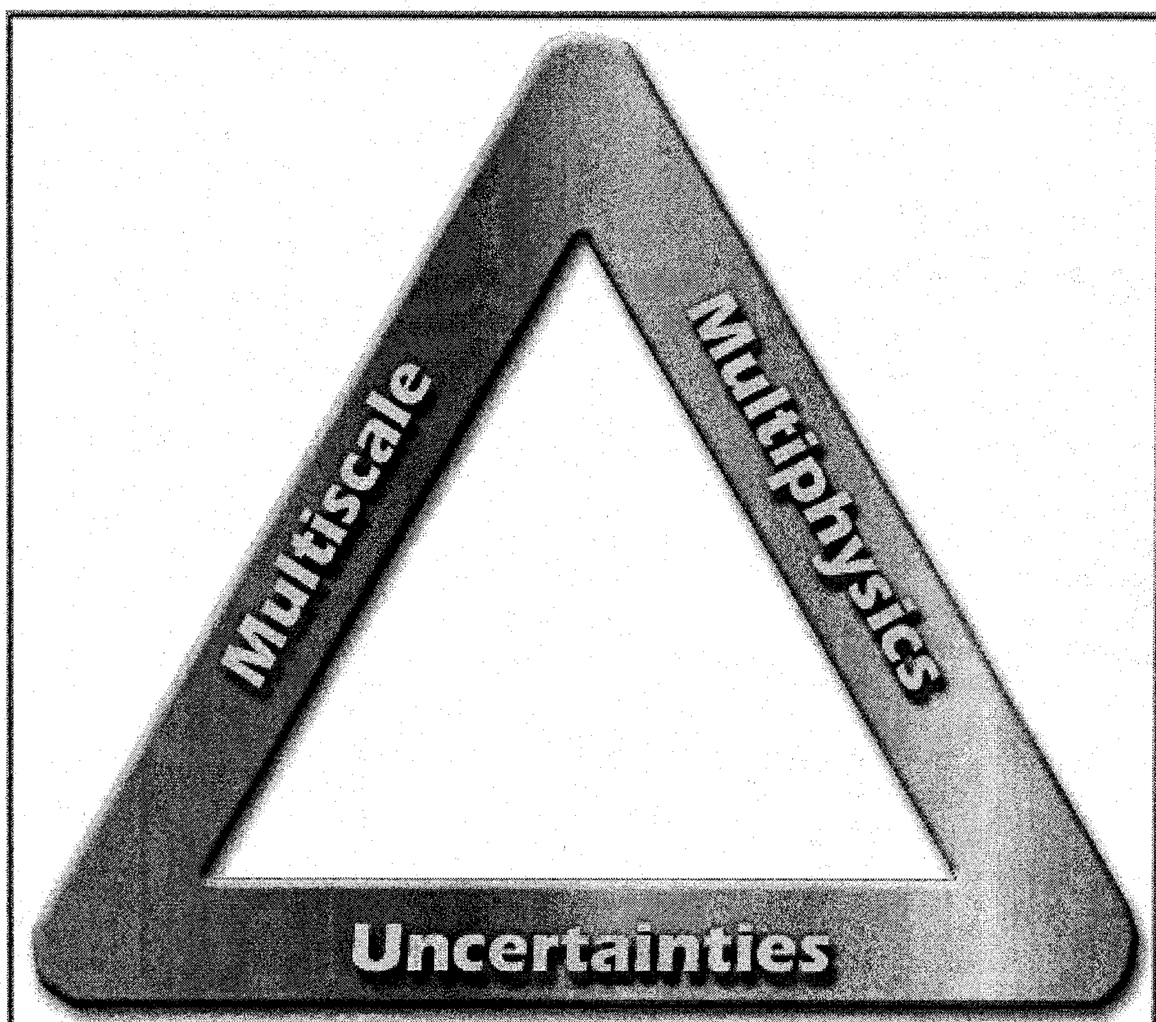

Figure 16

PRINCIPLE OF COMPLEXITY

One of the important consequences of uncertainty is its effect on precision. Three types of models can be identified depending on the complexity and the precision, namely: mathematical models, model-free methods, and fuzzy systems (Figure 17). In a typical complex system a combination of the three should be used. As the uncertainty and/or complexity of an engineering system increases, the ability to predict its response diminishes, until a threshold is reached beyond which precision and relevance become almost mutually exclusive. Consider, for example, numerical simulations in which sophisticated computational models are used for predicting the response, performance, and reliability of the engineering system, but the system parameters are little more than guesses. Such simulations can be characterized as Correct but Irrelevant Computations (CBIC); that is, forcing precision where it is not possible.

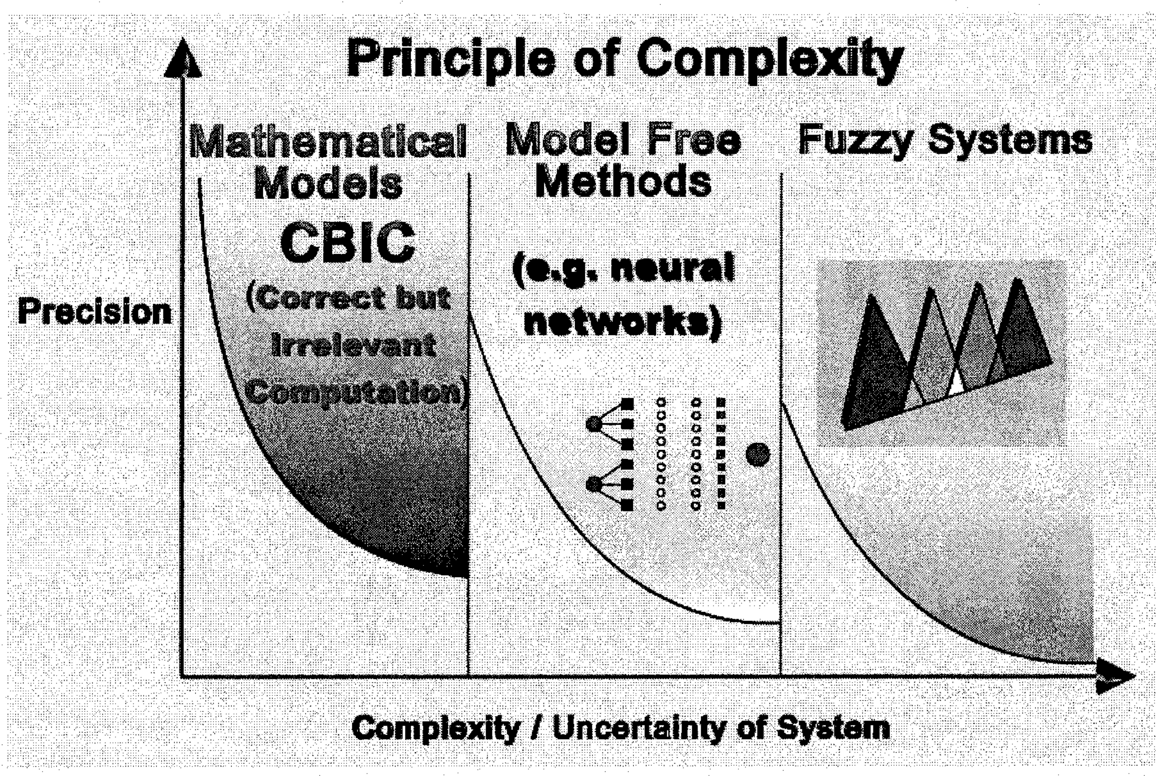

Figure 17

BOUNDING UNCERTAINTIES IN SIMULATION MODELS

Current synthesis approaches of simulation models involve a sequence of four phases (Figure18).

First – selection of the models, which includes decisions about modeling approach, level of abstraction, and computational requirements. The complexities arise due to:

- Multiconstituents, multiscale, and multiphysics material modeling,
- Integration of heterogeneous models,

Second – parameter identification. Data reduction techniques are used which incorporate uncertainties,

Third – model updating, or reducing uncertainty by improving either the model characteristics or the model itself, and

Fourth – Validation, in the sense of confirming that the model is an accurate representation of the real system.

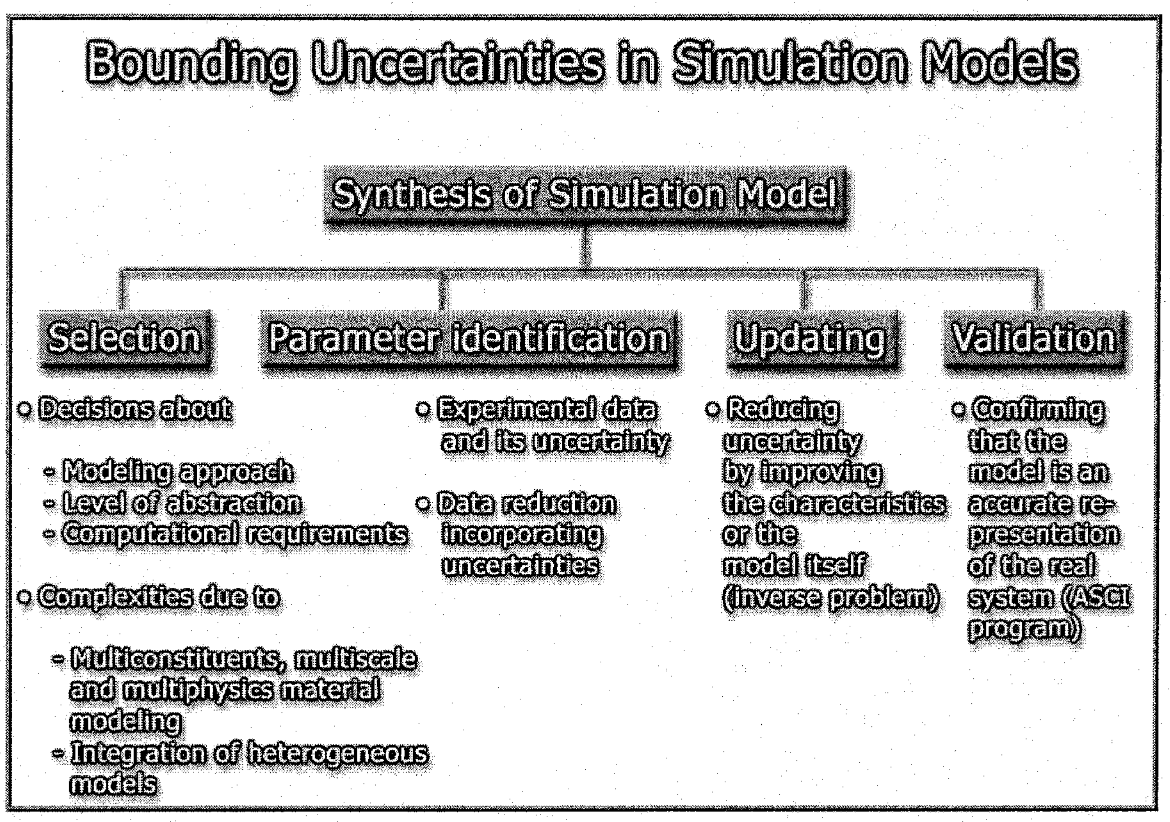

Figure 18

QUALITY CONTROL AND UNCERTAINTY MANAGEMENT IN THE MODELING AND SIMULATION OF COMPLEX SYSTEMS

The estimation of total uncertainty in the modeling and simulation of complex systems involves: a) identification and characterization of the sources of uncertainty, variability and error; b) uncertainty propagation and aggregation; and c) uncertainty quantification (Figure 19).

Herein *uncertainty* is defined as a deficiency in any phase of the modeling process due to lack of knowledge (model form or reducible uncertainty) increasing the knowledge base can reduce the uncertainty. The term *variability* is used to describe inherent variation associated with the system or its environment (irreducible or stochastic uncertainty) variability is quantified by a probability or frequency distribution. An *error* is defined as a recognizable deficiency that is not due to lack of knowledge. An error can be either acknowledged (e.g., discretization or round-off error), or unacknowledged (e.g., programming error).

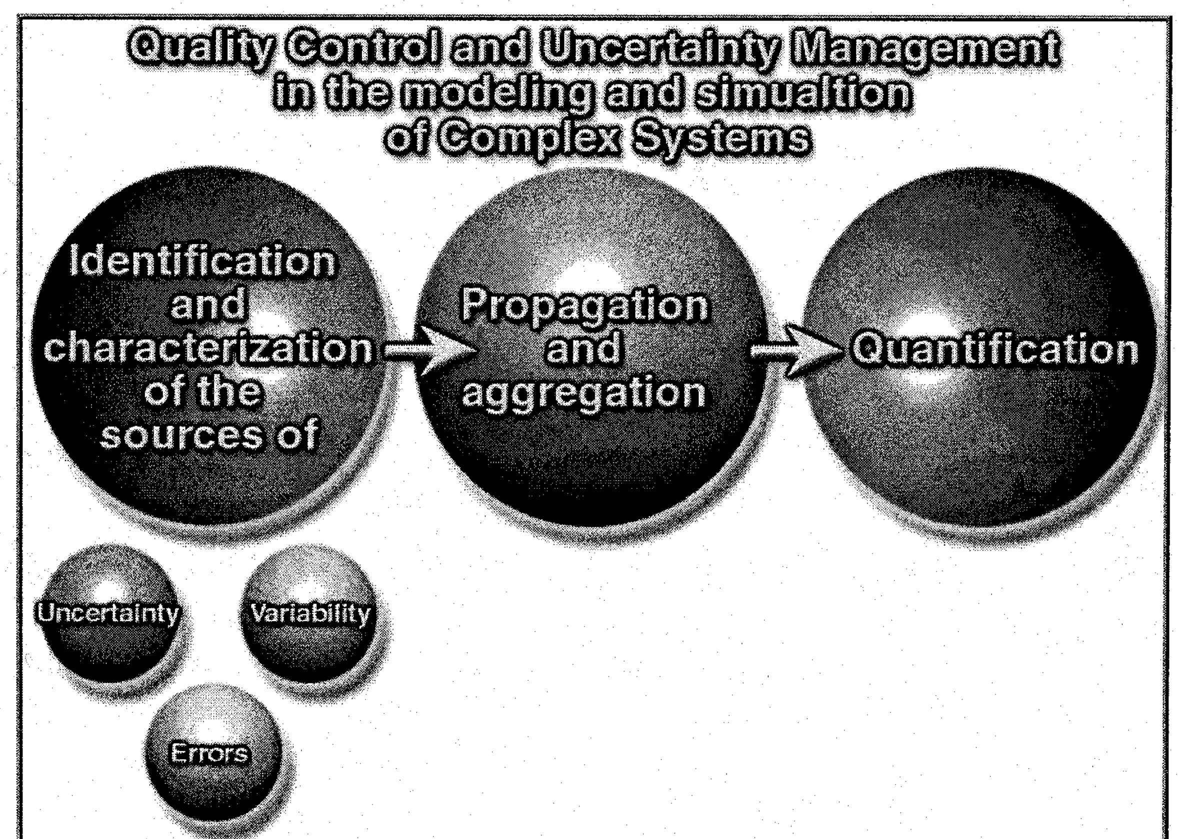

Figure 19

VERIFICATION AND VALIDATION OF NUMERICAL SIMULATIONS

Quantifying the level of confidence, or reliability and accuracy of numerical simulations has recently received increased levels of attention in research and engineering applications. During the past few years, new technology development concepts and terminology have arisen. Terminology such as virtual prototyping and virtual testing is now being used to describe computer simulation for design, evaluation and testing of new engineering systems.

The two major phases of modeling and simulation of an engineering system are depicted in Figure 20. The first phase involves developing a conceptual and mathematical model of the system. The second phase involves discretization of the mathematical model, computer implementation, numerical solution and representation or visualization of the solution. In each of these phases there are uncertainties, variabilities and errors.

Verification and validation are the primary methods for building and quantifying confidence in numerical simulations. *Verification* is the process of determining that a model implementation accurately represents the conceptual/mathematical model and the solution to the model. Correct answer is provided by highly accurate solutions. *Validation* is the process of determining the degree to which a model is an accurate representation of the real system. Correct answer is provided by experimental data.

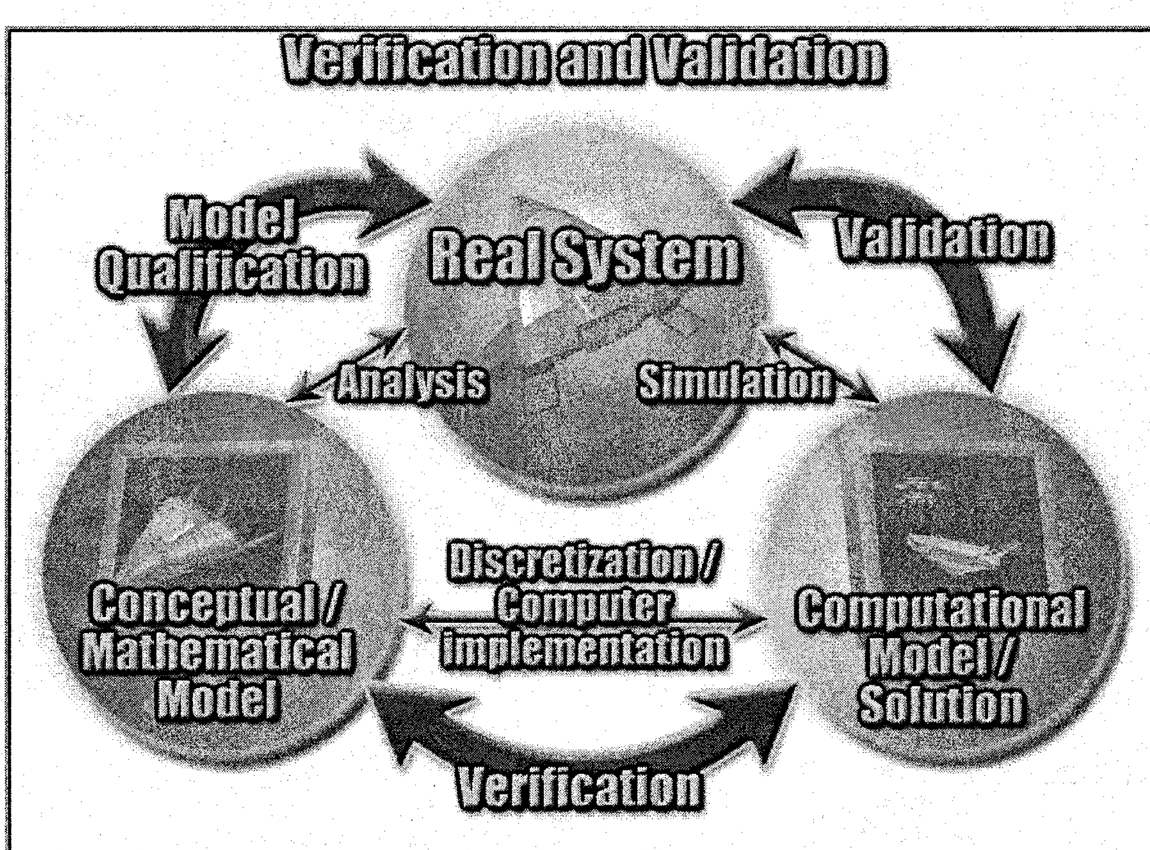

Figure 20

DESIGN OF EXPERIMENTS

These are systematic techniques for investigating (all possible) variations in system performance due to changes in system variables.

Two categories of system variables can be identified, namely, a) Inner-array variables, which are controllable; and, b) outer-array variables (also called noise factors), which are functions of environmental conditions, and are uncontrollable. Three categories of techniques can be identified: Regression analysis, statistical methods and Taguchi's method (Figure 21).

In Taguchi's method, the controllable variables are selected in such a way as to dampen the effect of the noise variables on the system performance. The method was originally developed as an industrial total quality control approach. Subsequently, it has found several other applications, including design optimization through variability reduction.

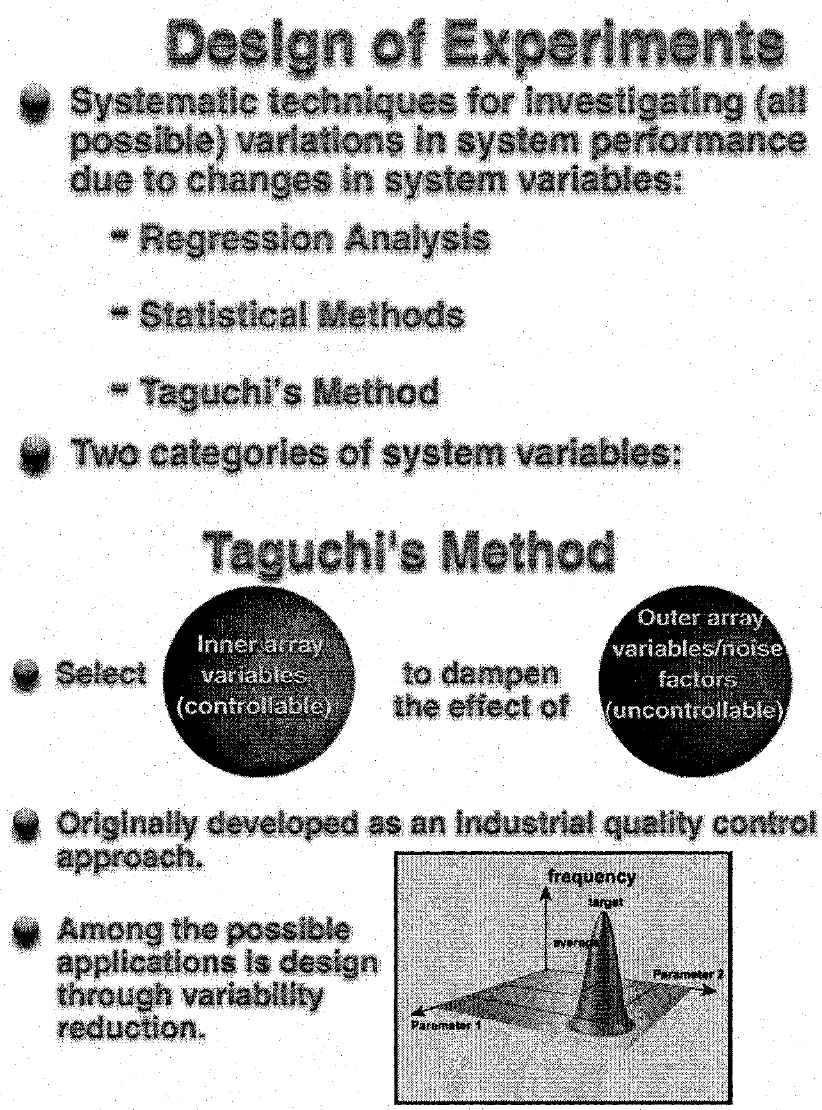

Figure 21

EDUCATION, TRAINING AND LEARNING

There has long been a philosophical gap between education and training. The goal of education was to impart high-level cognitive skills that would underpin lifelong learning. The goal of training was to bring performance up to a level that would let people successfully achieve tasks. Recently, however, began to emphasize the skills involved in lifelong learning, as evidence by continual-growth workshops and online training facilities on the Internet. In a sense, both education and training objectives fit in the larger classification of learning objectives (see figure 22).

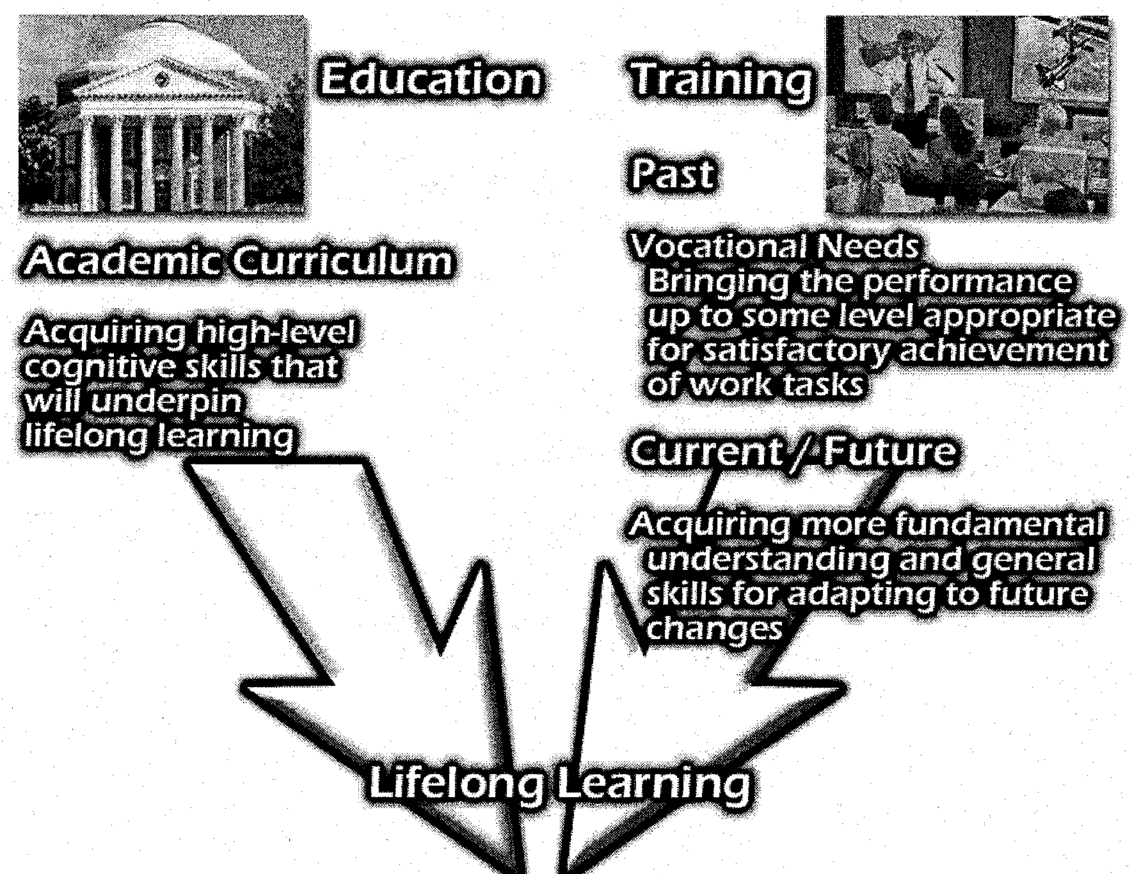

Figure 22

LEARNING OBJECTIVES, INSTRUCTIONAL MODELS AND TECHNOLOGIES

The desired outcome of learning can range from information transfer to skill and knowledge acquisition to the more ambitious goal of development of critical thinking and creativity skills. The instructional model and method used for accomplishing these goals vary from instructor-centered, learner-center to learning-team centered. In the learner-centered model, the learner is at the center of the learning process, and calls on many information sources. Learning-team center models include virtual classrooms and web-based distance learning models. The technologies employed in the three models are distribution, interactive and collaborative technologies, respectively (See Figure 23).

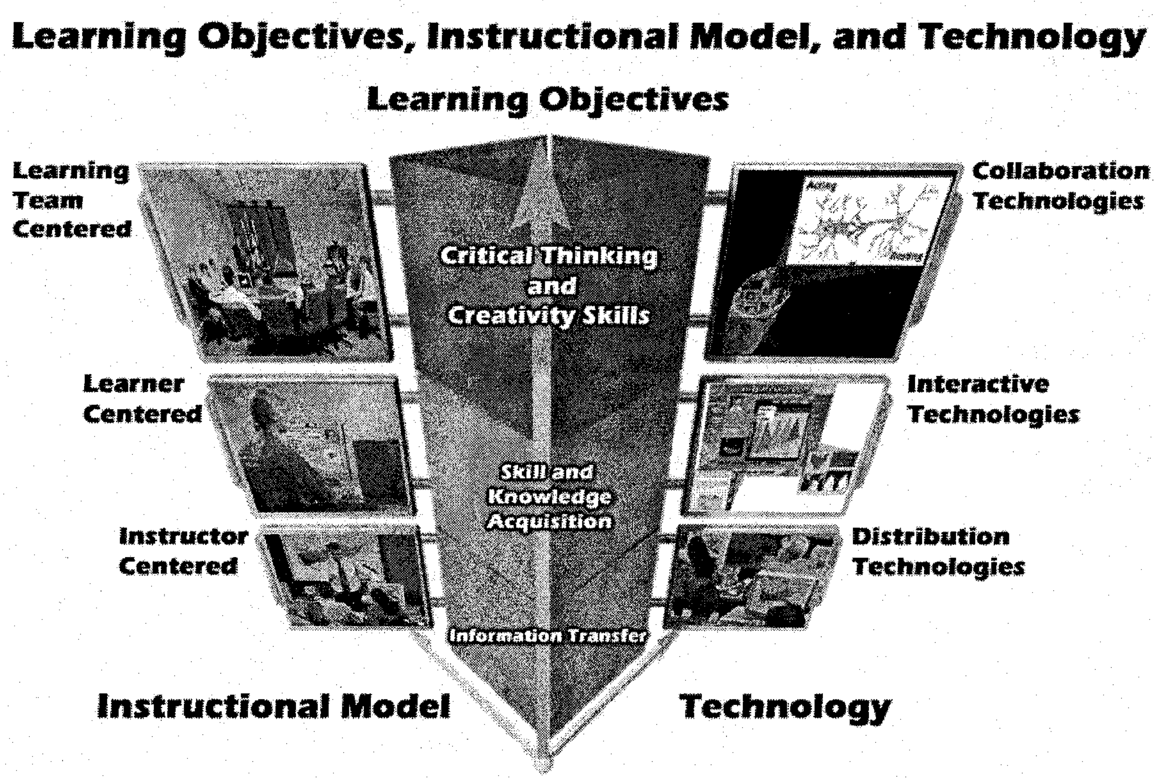

Figure 23

LEARNING NETWORKS

The convergence of computing, communication and information technologies is providing opportunities for creating effective environments for life-long learning through expanding the concept of a university which is, typically limited to a campus, to that of a learning network (Figure 24). In such a network, the classrooms are augmented by e-learning facilities (e.g., virtual classrooms); the libraries are expanded into intelligent knowledge repositories (with digital libraries and intelligent search and information visualization capabilities); the physical test and experimental facilities are augmented with access to more elaborate facilities at government labs, along with computer simulation of these facilities; and Immersive telepresence technology is used to provide interaction with geographically dispersed instructors and learners at other locations.

Figure 24

ACTIVITIES OF LEARNING NETWORKS

The learning networks can significantly enhance the effectiveness of engineering education, by changing the way three of the major functions of a university are carried out, namely, development of content for courses, packaging courses into curricula and programs, and delivery of these programs to learners (Figure 25).

Each course is divided into self-contained learning modules, and a consortium is established for generating the best content for each of the learning modules. Advanced instructional technology; modeling, simulation and visualization facilities and authoring tools are used in the development of modules.

The learning modules are then packaged into disciplinary and interdisciplinary courses and training programs to satisfy the needs of diverse groups.

The packaged modules are presented to individuals as well as groups of learners. Collaboration and interaction is made available at many levels, both synchronous and asynchronous.

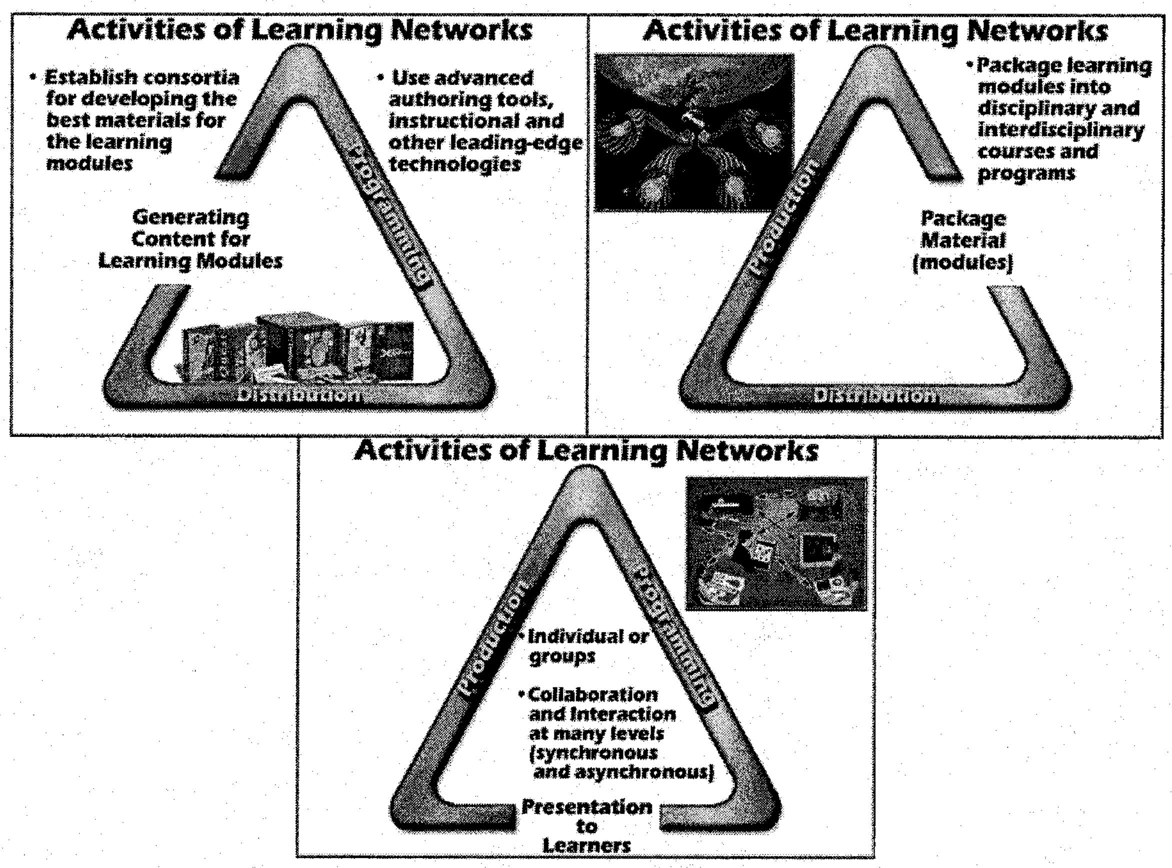

Figure 25

ADVANCED LEARNING ENVIRONMENTS

In order to meet the life long learning demands of the future and broaden the awareness among the researchers and engineers of nondeterministic approaches, three categories of learning environments are needed; namely, expert led group learning environment; self paced individual learning environment; and collaborative learning environment (Figure 26). The three environments, in combination, can reduce the time and cost of learning, as well as sustain and increase worker competencies in high tech organizations.

The human instructors in these environments will serve many roles, including inspiring, motivating, observing, evaluating, and steering the learners, both individually and in distributed teams.

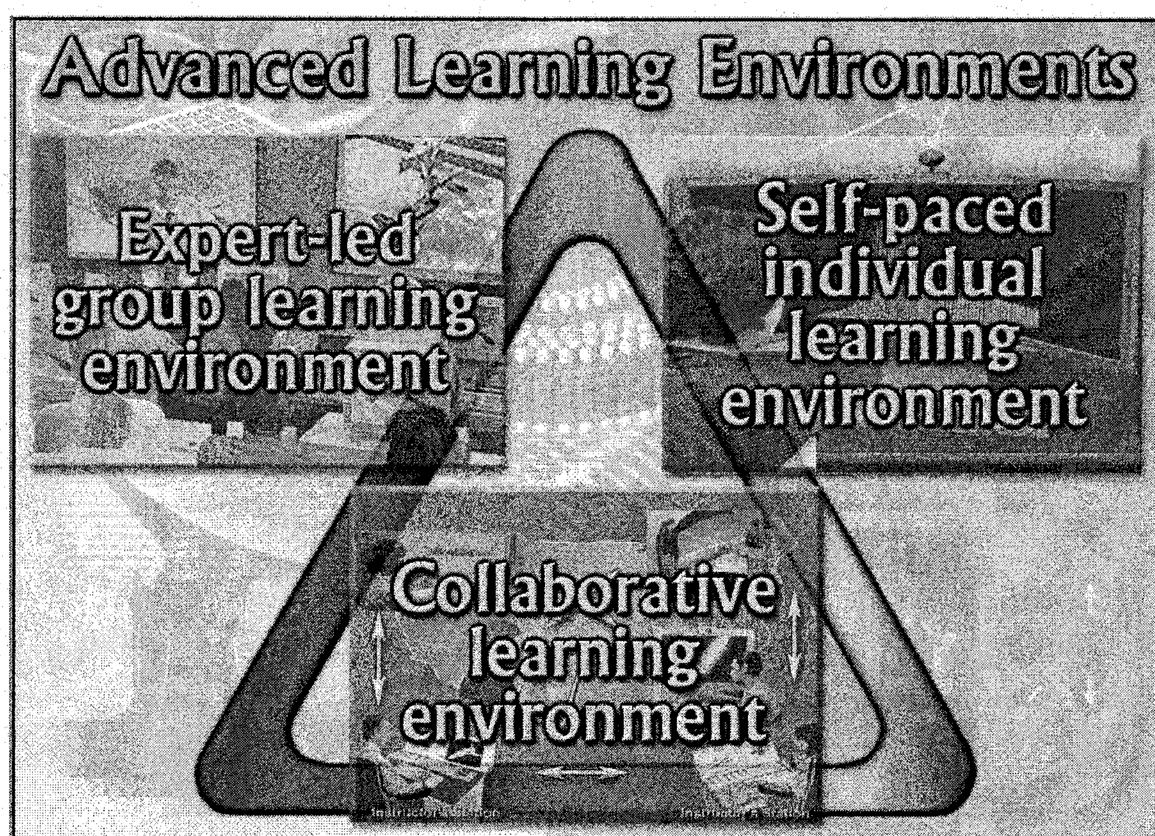

Figure 26

EXPERT LED LEARNING ENVIRONMENT

The human instructors in expert-led distributed learning in a virtual environment serve as coaches, guides, facilitators, and course managers. Their presentations focus on a broad overview of the topic and its diverse applications (Figure 27), and end with more penetrating, what-if questions that can enhance the critical thinking and creativity of the learners. Elaborate visualization and multimedia facilities are used in the presentations. Routine instructional and training tasks are relegated to the self-paced individual learning environment.

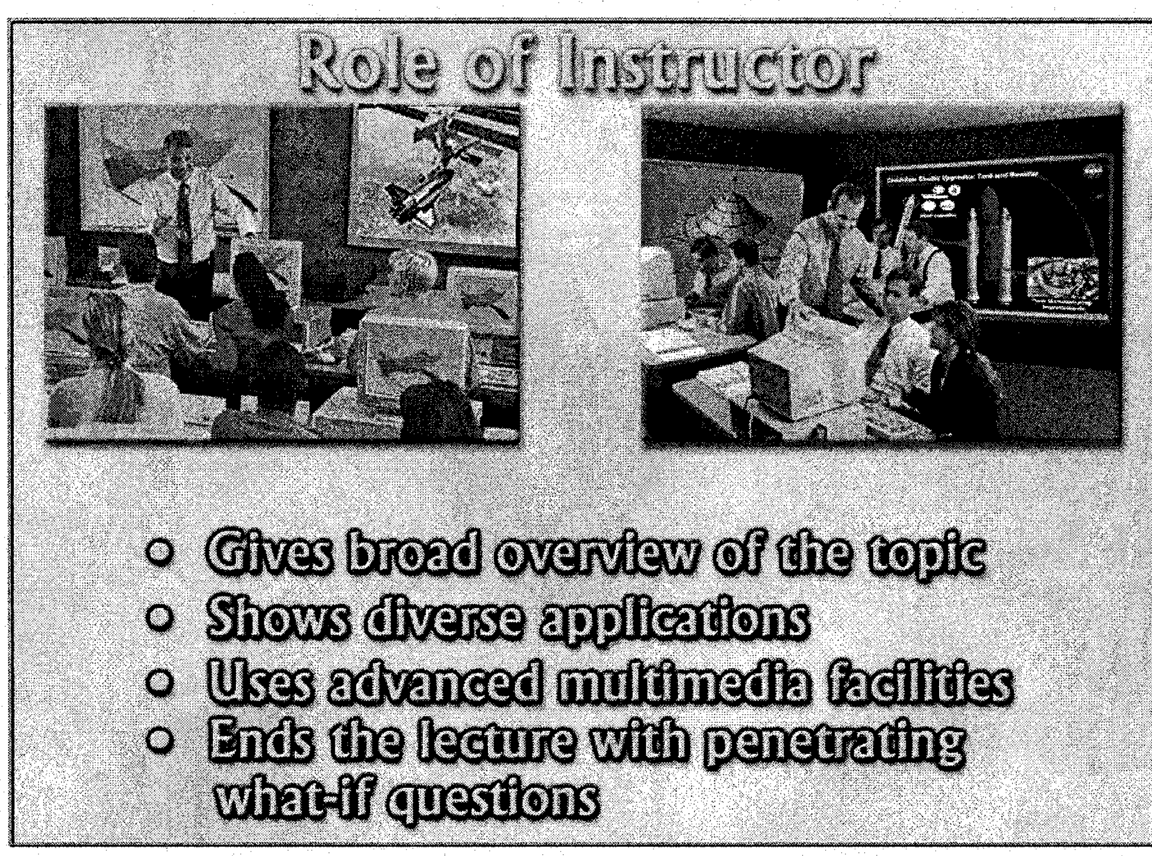

Figure 27

SELF-PACED LEARNING ENVIRONMENT

The individual learning environment engages the learner and provides a high degree of tailored interactivity. It can be used for self-paced instruction of routine material not covered in the lecture. Using virtual instructors assigned by the human instructors can enhance such instruction. It can be used to study the effect of various types of uncertainties on the system performance using advanced visualization, multimedia and multisensory immersive facilities. The individual learning environment can serve to carry out numerical and virtual experiments - computer simulation of physical experiments (Figure 28).

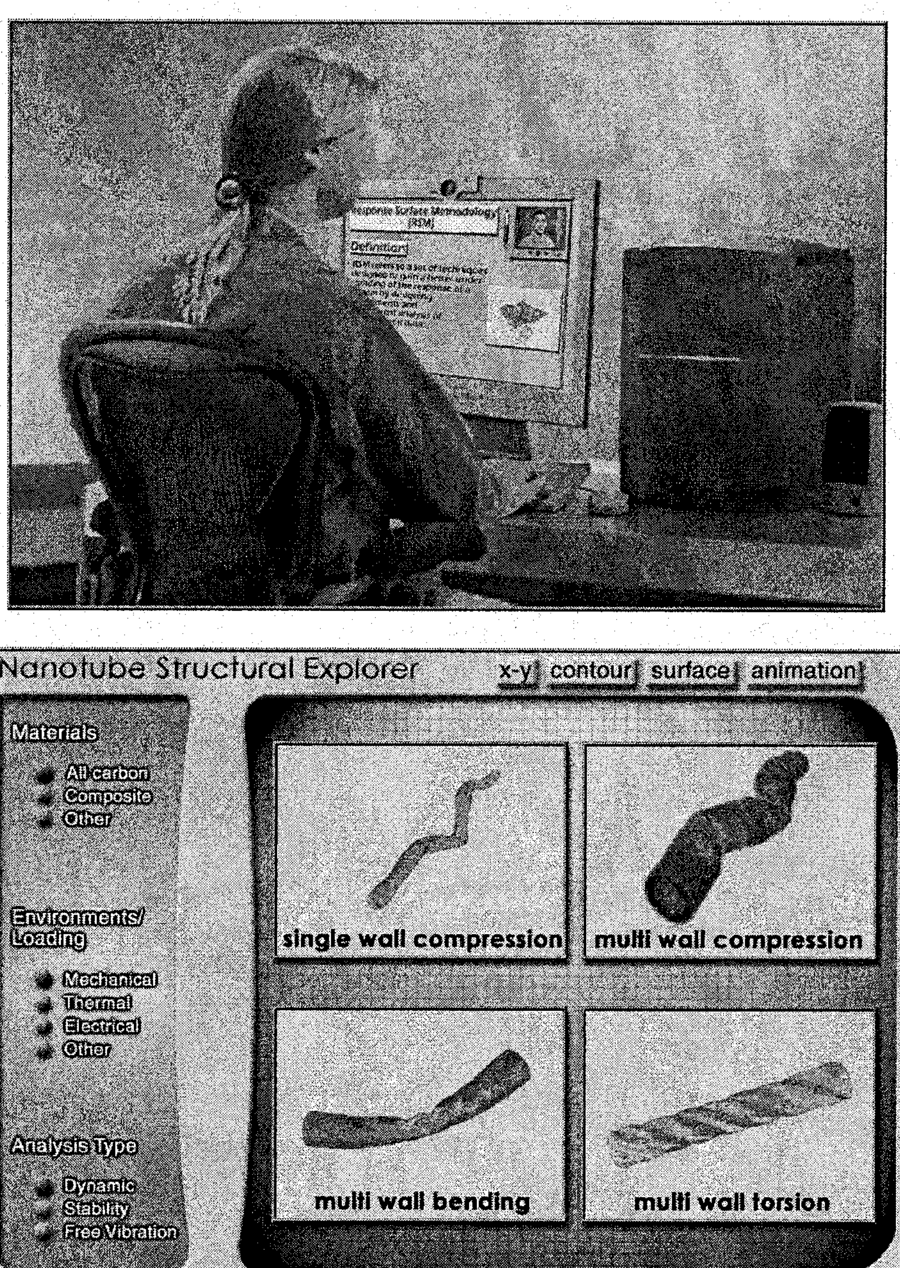

Figure 28

COLLABORATIVE / DISTRIBUTED LEARNING ENVIRONMENT

Collaborative learning environments teach teamwork and group problem solving. Instructors and learners can be geographically dispersed. Eventually, they can be brought together through immersive telepresence facilities to share their experiences in highly heterogeneous environments involving different computing platforms, software and other facilities, and they will be able to work together to design complex engineering systems beyond what is traditionally done in academic settings. Because participants can be virtually collocated without leaving their industry and government laboratories, collaborative learning environments can enable the formation of learning networks linking universities, industry and government labs. The ultimate goal of these learning facilities is to create an intellectual environment where academic and experiential learning are effectively and efficiently co-mingled. In such an environment, academic rigor is learned in concert with professional job performance, and academic complexities are addressed within the industrial concern (Figure 29).

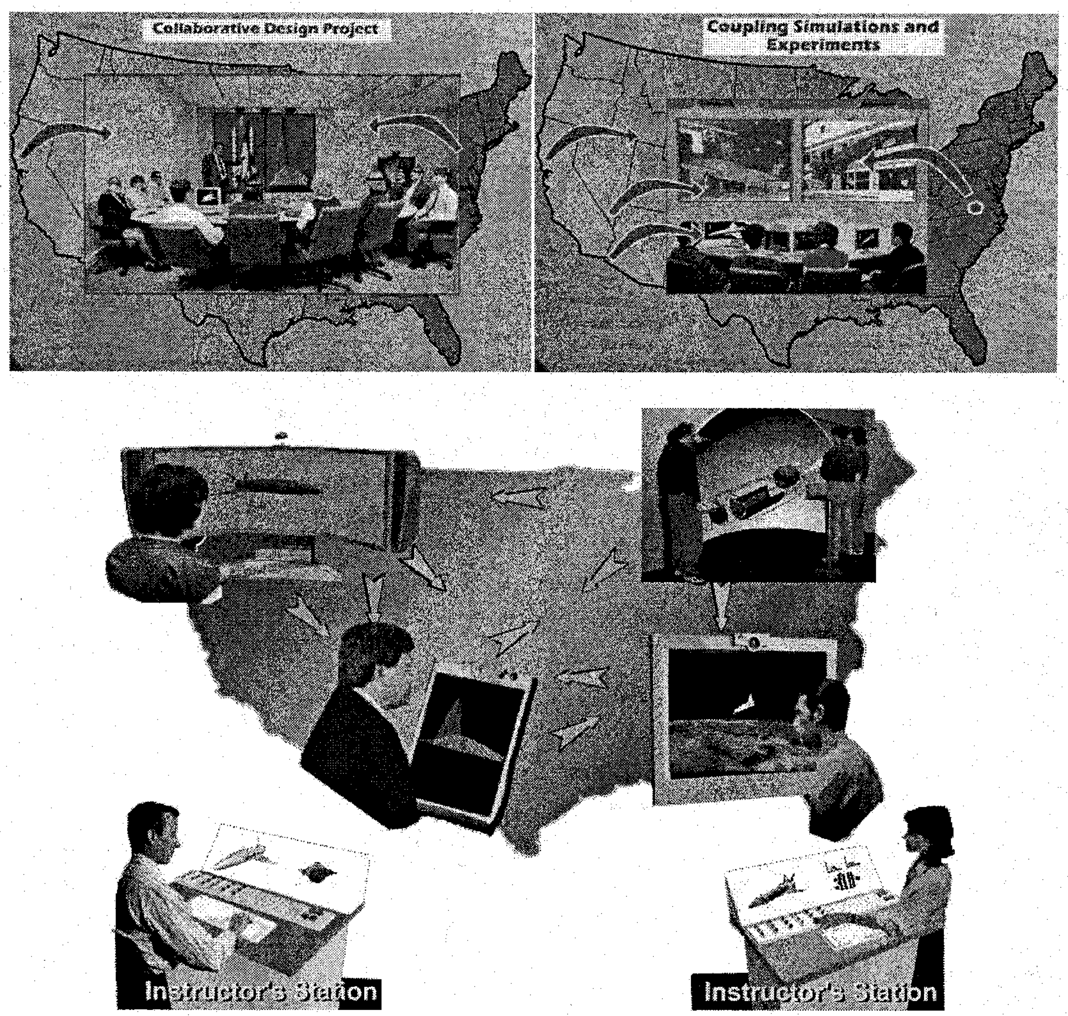

Figure 29

VIRTUAL CLASSROOM

Online training and virtual classrooms are typically used to provide learning environments with custom self-instruction, flexible tutorial support, and choice of both the place and time of learning. Three categories of facilities are used in these environments; namely: *instruction*, including multimedia lectures, links to other resources and tools for searching, browsing, and using archived knowledge; *communication*, including email, UseNet, chat centers, video and Internet conferencing; and *course management and performance evaluation* (Figure 30).

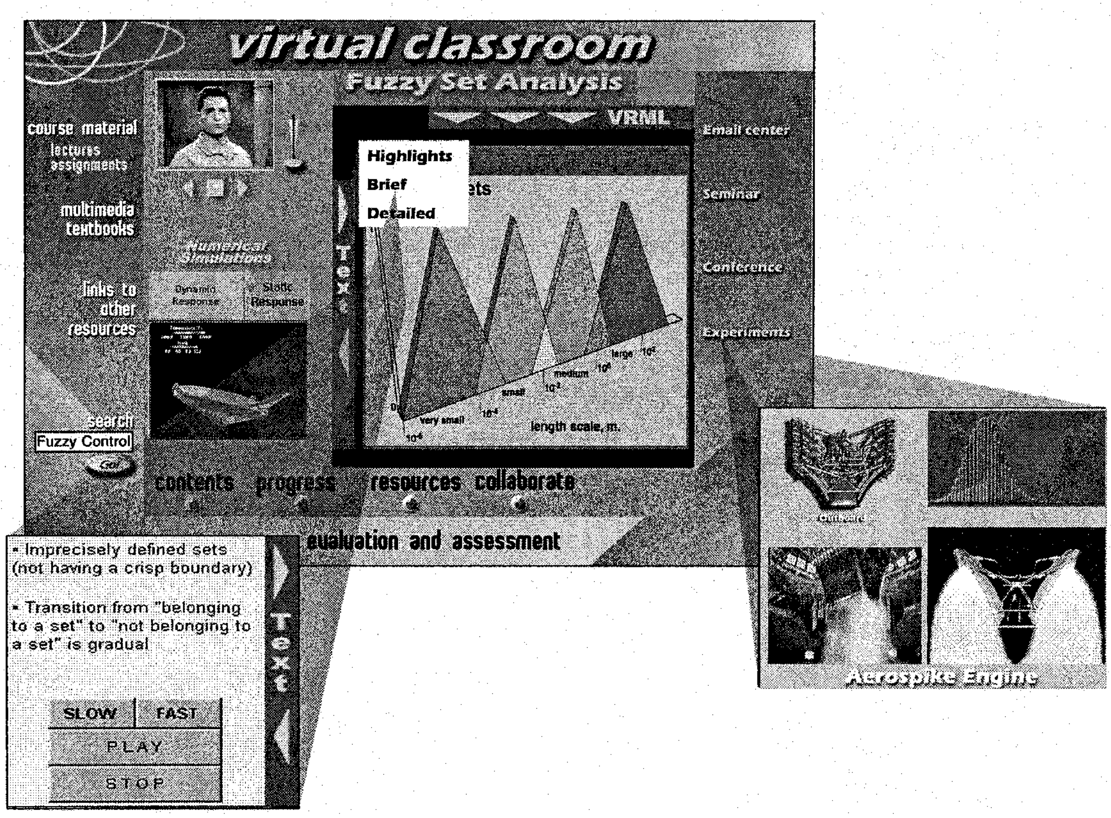

Figure 30

NONDETERMINISTIC APPROACHES RESEARCH AND LEARNING NETWORKS

The realization of the full potential of nondeterministic approaches in the design and development of future complex systems requires, among other things, the establishment of research and learning networks. The networks connect diverse, geographically dispersed teams from NASA, other government labs, university consortia, industry, technology providers, and professional societies (Figure 31).

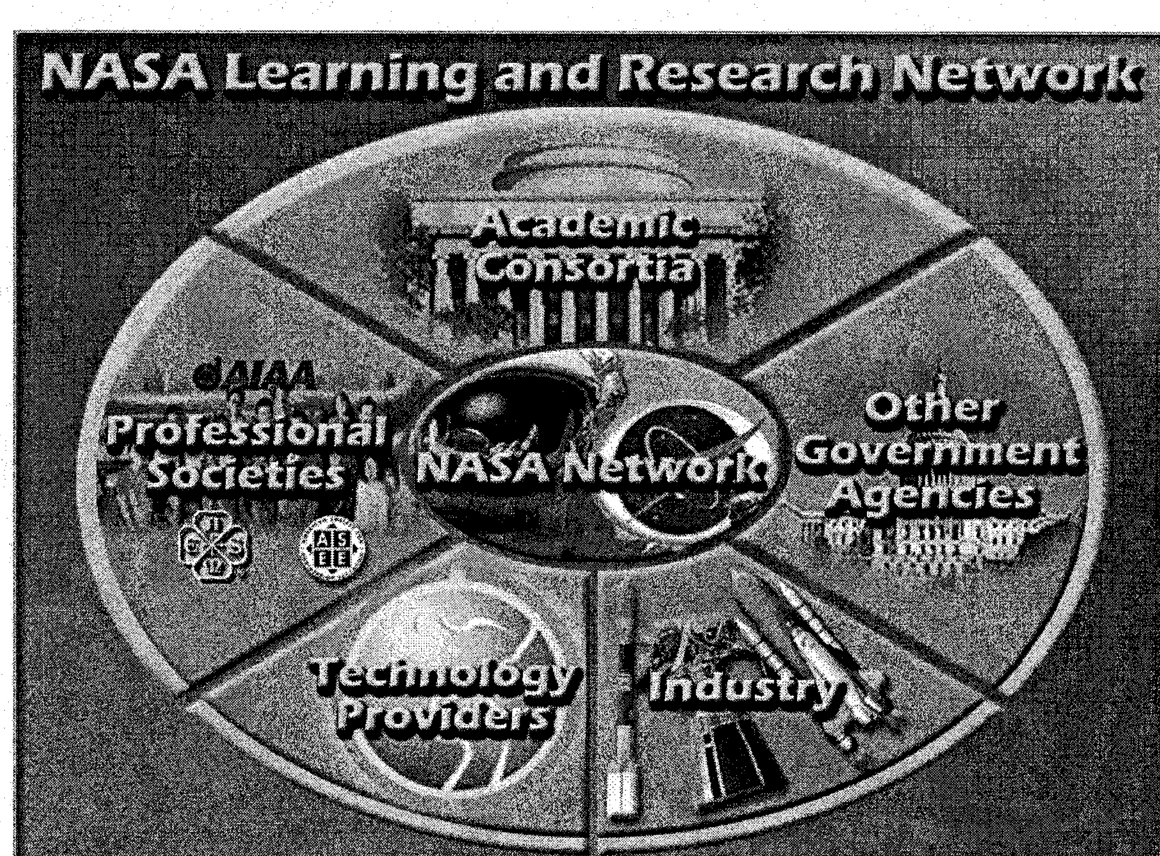

Figure 31

EVOLUTION OF NEW TECHNOLOGY

The nondeterministic approaches and their associated technologies, as any other technology, have gone through three phases. The first is that of *naïve euphoria* - unrealistic expectations resulting from overreaction to immature technology. The second is *cynicism*, or frustration associated with unmet expectations. The third is that of *realistic expectations* – gradually realizing the true benefits from the technologies (Figure 32).

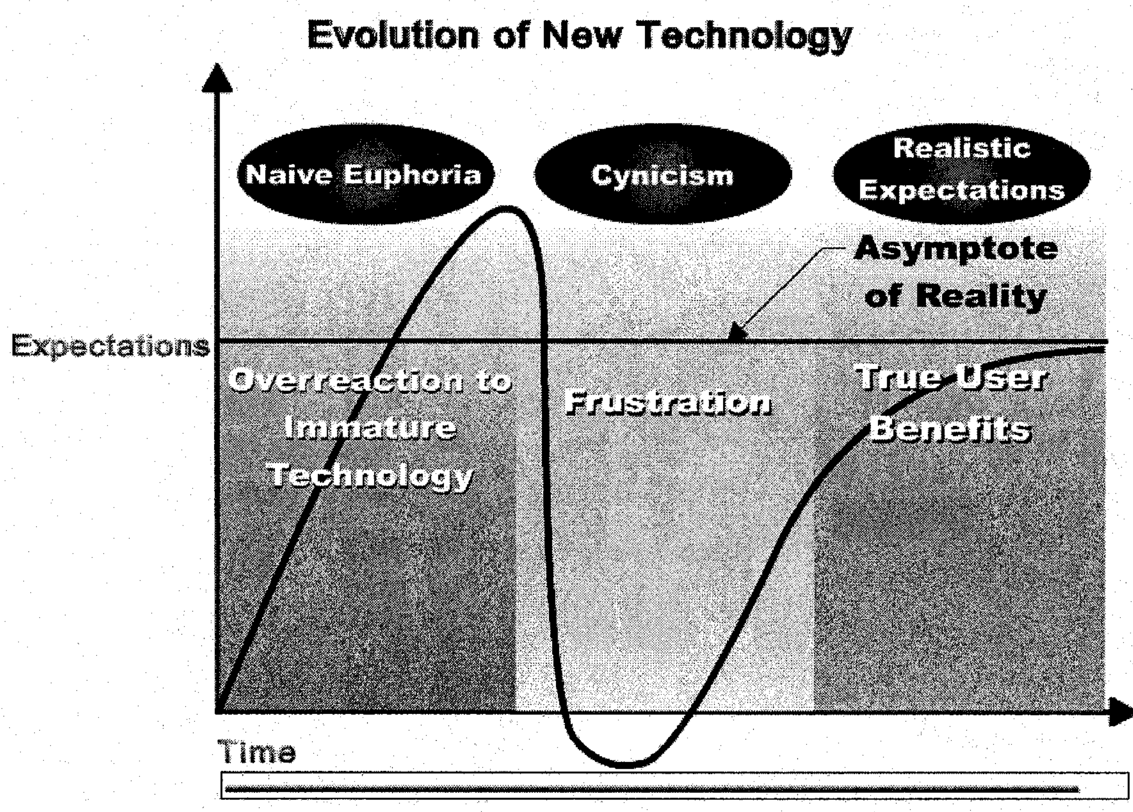

Figure 32

OBJECTIVES AND FORMAT OF WORKSHOP

The objectives of the workshop are to: a) provide a broad overview of nondeterministic approaches, uncertainty management methodologies, reliability assessment and risk management techniques, and b) identify the potential of these technologies to future aerospace systems (Figure 33). The workshop, including sixteen presentations and three exhibits, illuminate some of the key issues in nondeterministic approaches and provide fresh ideas for future research and development (Figure 34).

Objectives and Format of Workshop

Objectives

- Overview of diverse activities in Nondeterministic Approaches
- Identify potential for future aerospace systems

Format

- 16 presentations, 7 sessions
- 3 Exhibits

Proceedings

- Printed (NASA CP)
- Electronic

Figure 33

INFORMATION ON NONDETERMINISTIC APPROACHES

Extensive literature no exists on nondeterministic approaches, uncertainty management methodologies, reliability assessment and risk management techniques. A short list of reports, survey papers, monographs and books is given subsequently.

1. Oberkampf, William L., DeLand, Sharon M., Rutherford, Brian M., Diegert, Kathleen V., and Alvin, Kenneth F., "*Estimation of Total Uncertainty in Modeling and Simulation*", Sandia Report, April 2000.
2. Oberkampf, W.L. and Blottner, F. G., "*Issues in Computational Fluid Dynamics Code Verification and Validation*", AIAA Journal, Volume 36, Number 5, pp. 687 – 695.
3. Natke, H. Gunther and Ben-Haim, Yakov, *Uncertainty: Models and Measures: Proceedings of the International Workshop held in Lambrecht, Germany July 22 – 24, 1996*, Akademie Verlag, GmbH, Berlin, 1997.
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5. Coleman, Hugh W. and Steele, W. Glenn, Jr., *Experimentation and Uncertainty Analysis for Engineers,* 2nd Edition, John Wiley & Sons, Inc., New York, 1999.
6. Roy, Ranjit K., "*A Primer on the Taguchi Method*", Competitive Manufacturing Series, Van Nostrand Reinhold, New York, 1990.
7. Sundararajan, C. Raj, Ph.D., *Probabilistic Structural Mechanics Handbook – Theory and Industrial Applications*, Chapman & Hall, New York, 1995.
8. Modarres, Mohammad, Kaminskiy, Mark, and Krivtsov, Vasiliy, *Reliability Engineering and Risk Analysis – A Practical Guide*, Marcel Dekker, Inc., New York, 1999.
9. Ramakumar, R., *Engineering Reliability: Fundamentals and Applications*, Prentice Hall, New Jersey, 1993.
10. Knezevic, Jexdimir, *Reliability, Maintainability and Supportability: A Probabilistic Approach*, McGraw-Hill Book Company, New York, 1993.

Ignorance and Uncertainty Types in Designing Future Space Missions and Systems

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INTRODUCTION AND OBJECTIVE

Future systems will require engineers to design them, test their performance, and assess their robustness and vulnerability in a simulated environment. Simulation requires validated building blocks for materials behavior, physical laws, environment-system interaction, unit performance, and system performance. At every level and stage of the simulation process, verification and validation are needed that should include ignorance analysis, and uncertainty analysis and modeling. Example systems include our nuclear weapon stockpile, space stations, satellites, space missions, etc.

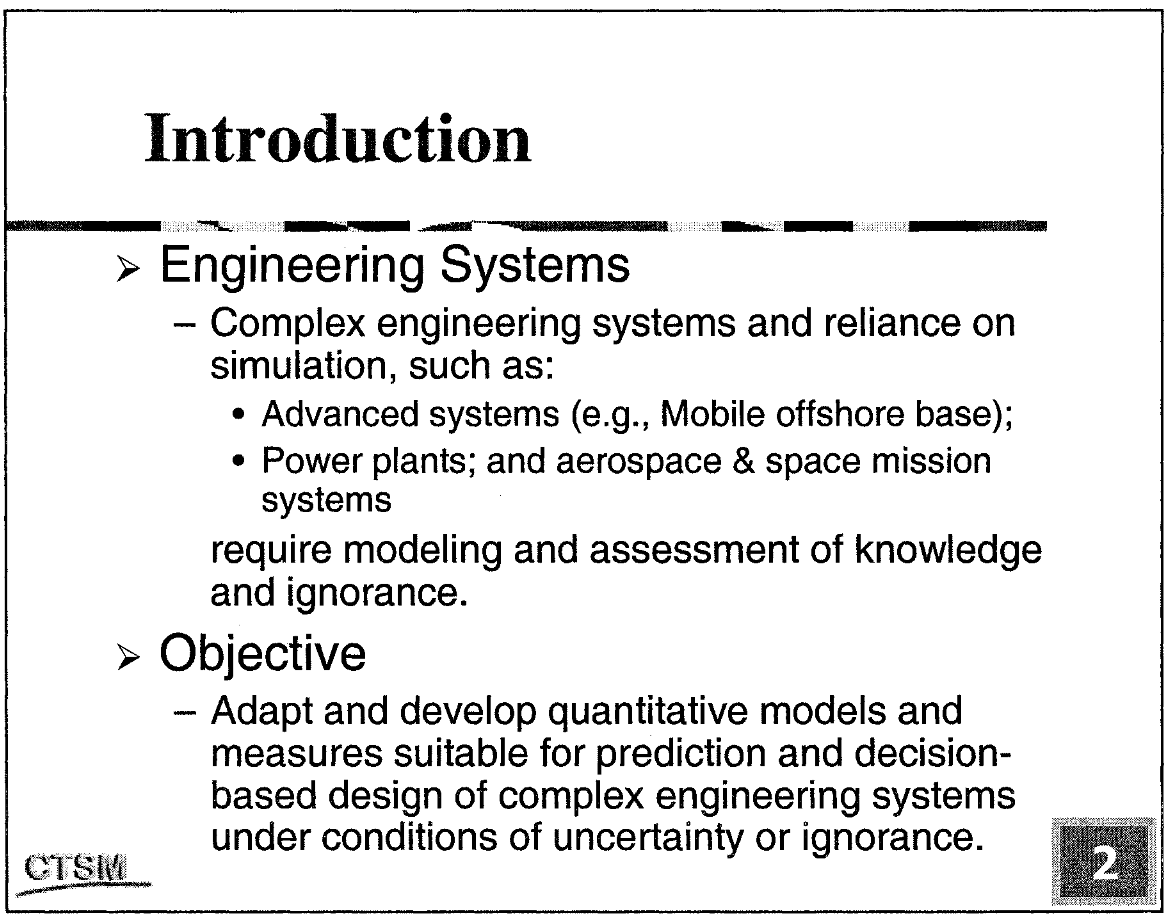

Figure 1

SYSTEM BREAKDOWN OF SHIPS

An example breakdown is provided for the functions of a ship. A work breakdown structure is also provided for illustration purposes.

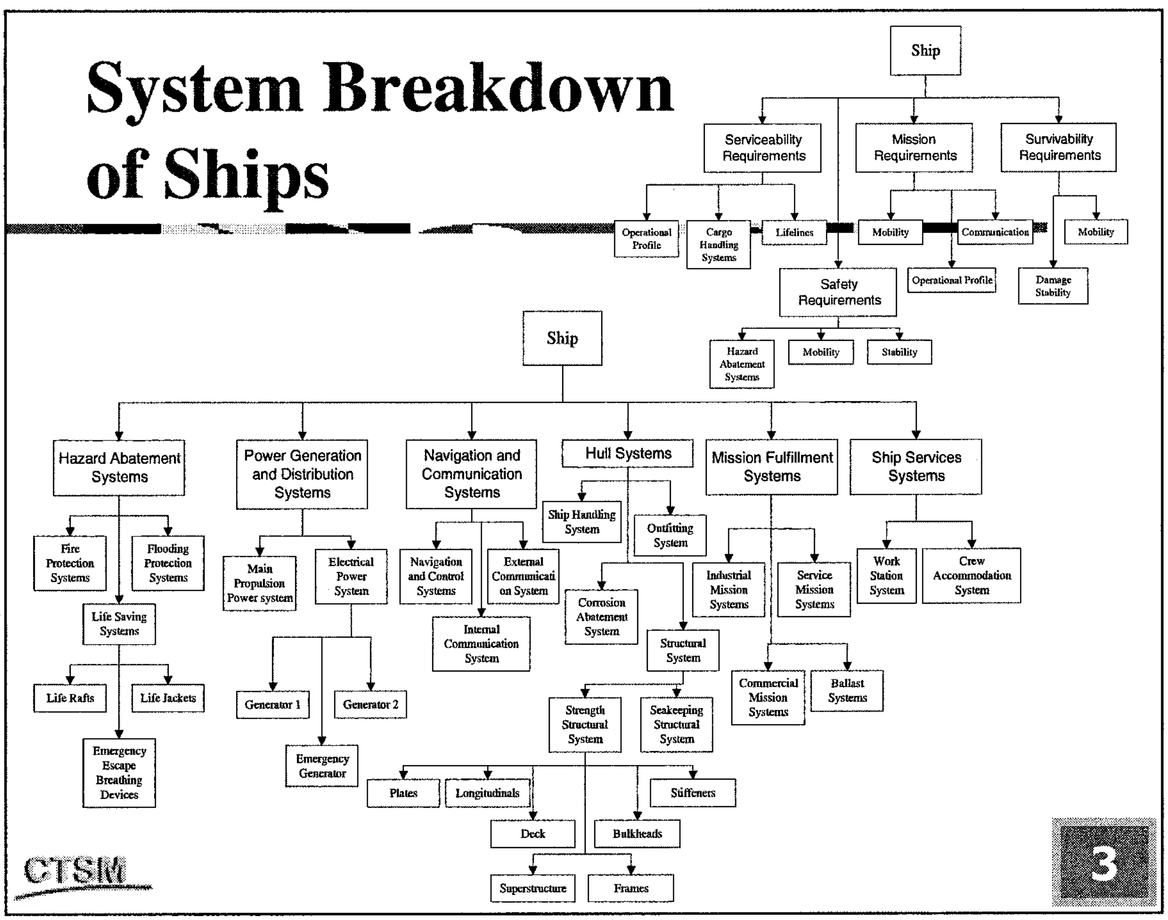

Figure 2

SYSTEM BREAKDOWN OF DAMS

An example breakdown is provided for the functions of a dam. A work breakdown structure is also provided for illustration purposes.

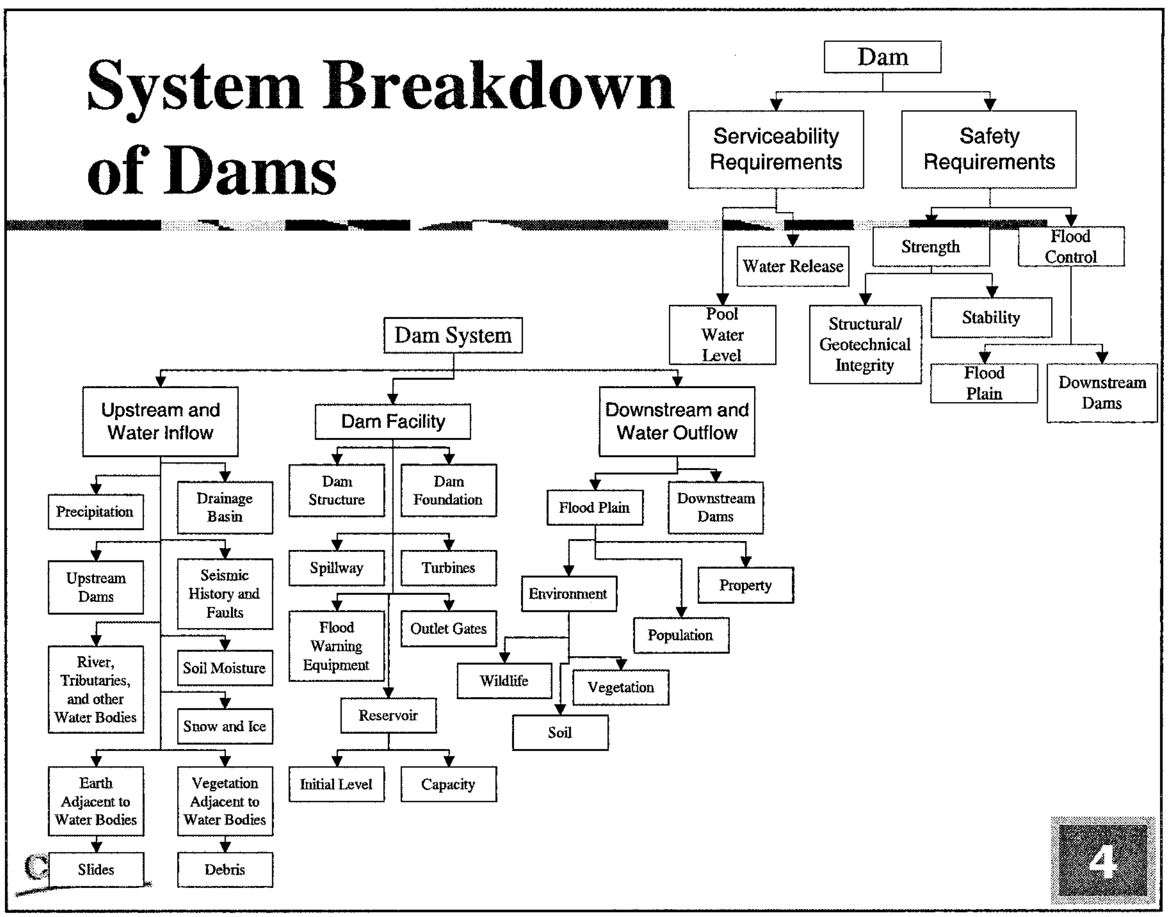

Figure 3

LIFECYCLE OF NASA ENGINEERING SYSTEMS

The phases of the lifecycle of NASA systems are provided in this viewgraph covering pre-phase and phase A. The details of these phases are listed.

Lifecycle of NASA Engineering Systems

- Pre-phase A. Advanced Studies
  - identify missions consistent with the NASA charter
  - identify and involve users
  - perform preliminary evaluations of possible missions
- Phase A. Conceptual Design Studies
  - preparation of mission needs statements
  - development of preliminary system requirements
  - identification of alternative operations and logistics concepts
  - identification of project constraints and system boundaries
  - consideration of alternative design concepts
  - demonstrating that credible, feasible designs exist

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Figure 4

LIFECYCLE OF NASA ENGINEERING SYSTEMS

The phases of the lifecycle of NASA systems are provided in this viewgraph covering phases B, C, D, E, and F. The details of these phases are listed.

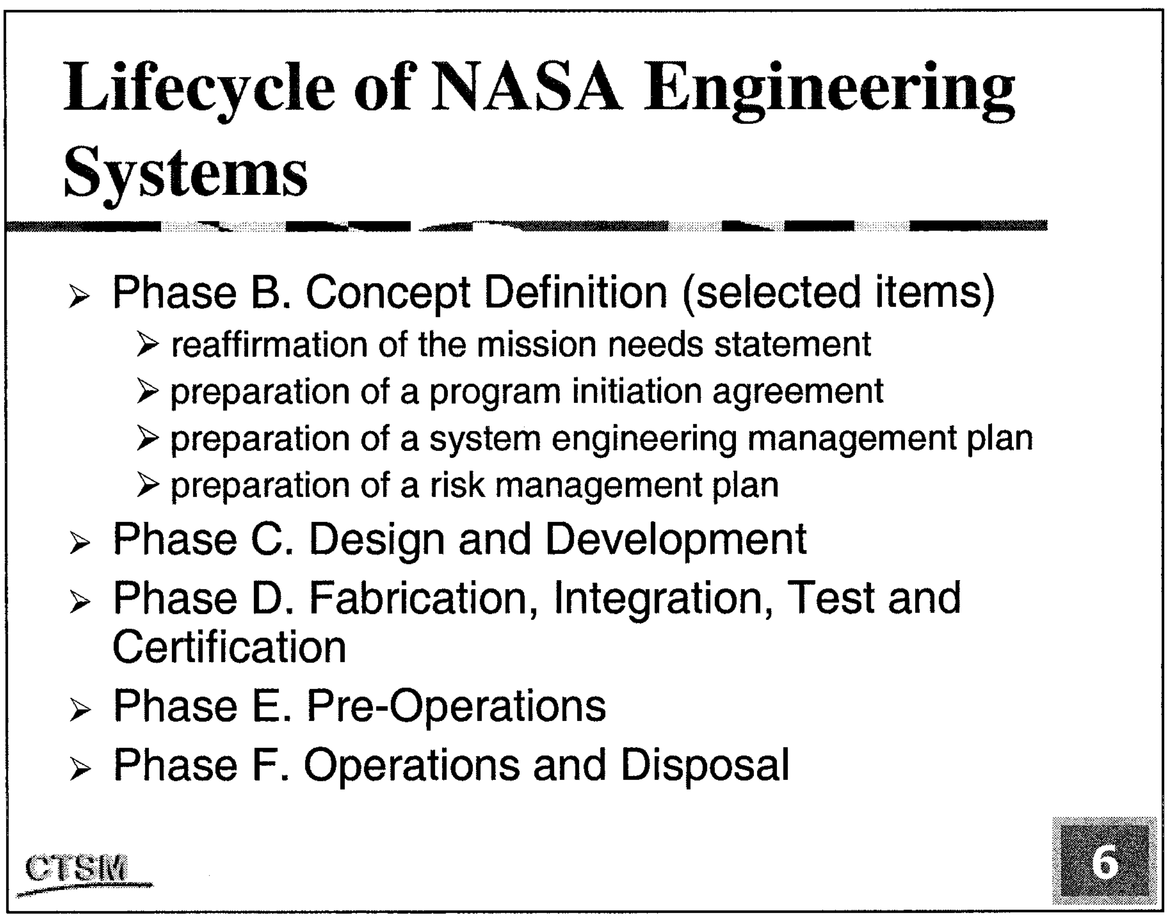


Figure 5

MODELING & SIMULATION OF ENGINEERING SYSTEMS

Modeling and simulation of engineering systems consists of several steps. These steps are key to the processes of model qualification, verification and validation. The processes of qualification, verification and validation are shown in the figure. The verification process consists of three stages: conceptual model verification, design verification, and code verification. The verification can be done by comparison and test of agreement between the computational model and solution, and results from benchmark (analytical or very accurate numerical solutions) of simplified model problems. The validation consists of two stages: conceptual model validation, and results validation that can be done by expert opinion solicitation. The objective herein is to adapt and develop quantitative models and measures suitable for prediction and decision-based design of complex engineering systems under conditions of uncertainty or ignorance.

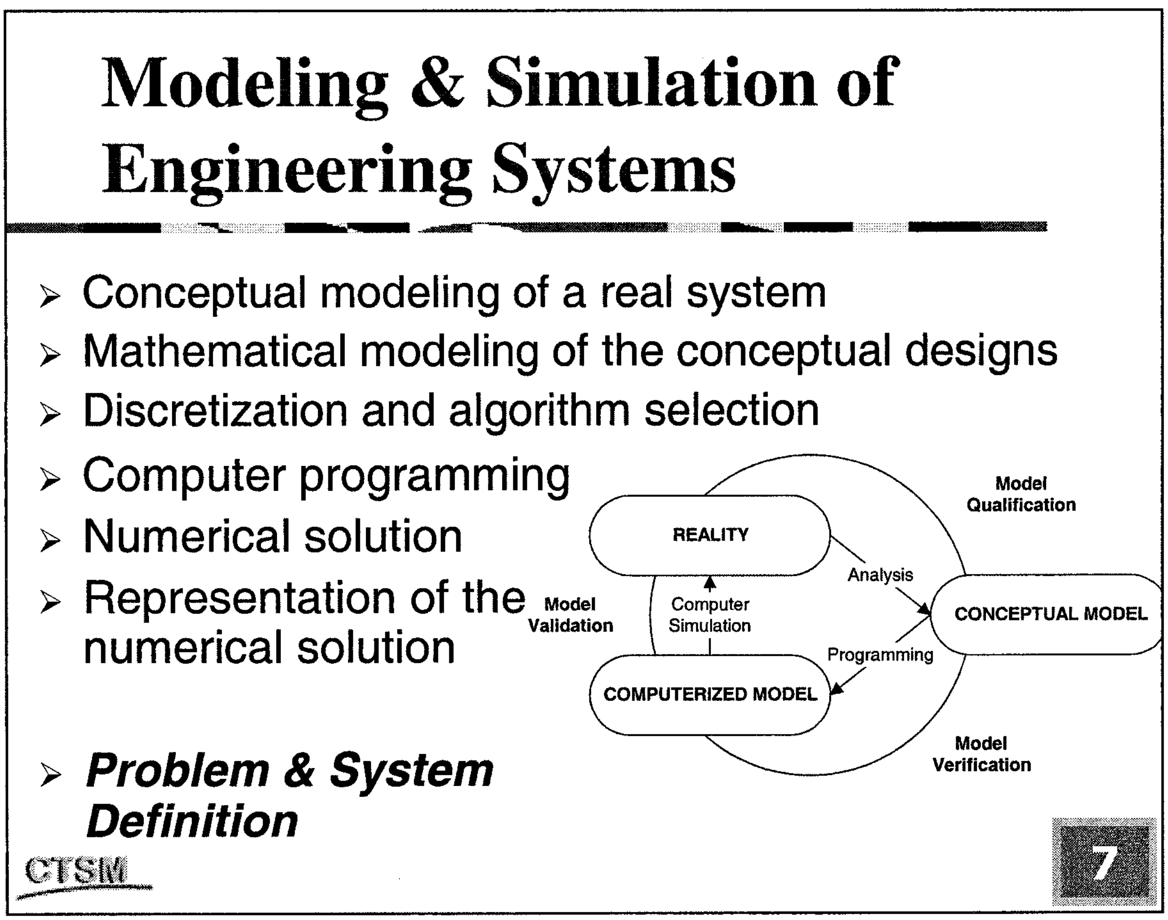


Figure 6

KNOWLEDGE NEEDS FOR SOLVING PROBLEMS AT THE SYSTEM LEVEL

Problem definition and abstraction are key elements to problem solving and knowledge construction.

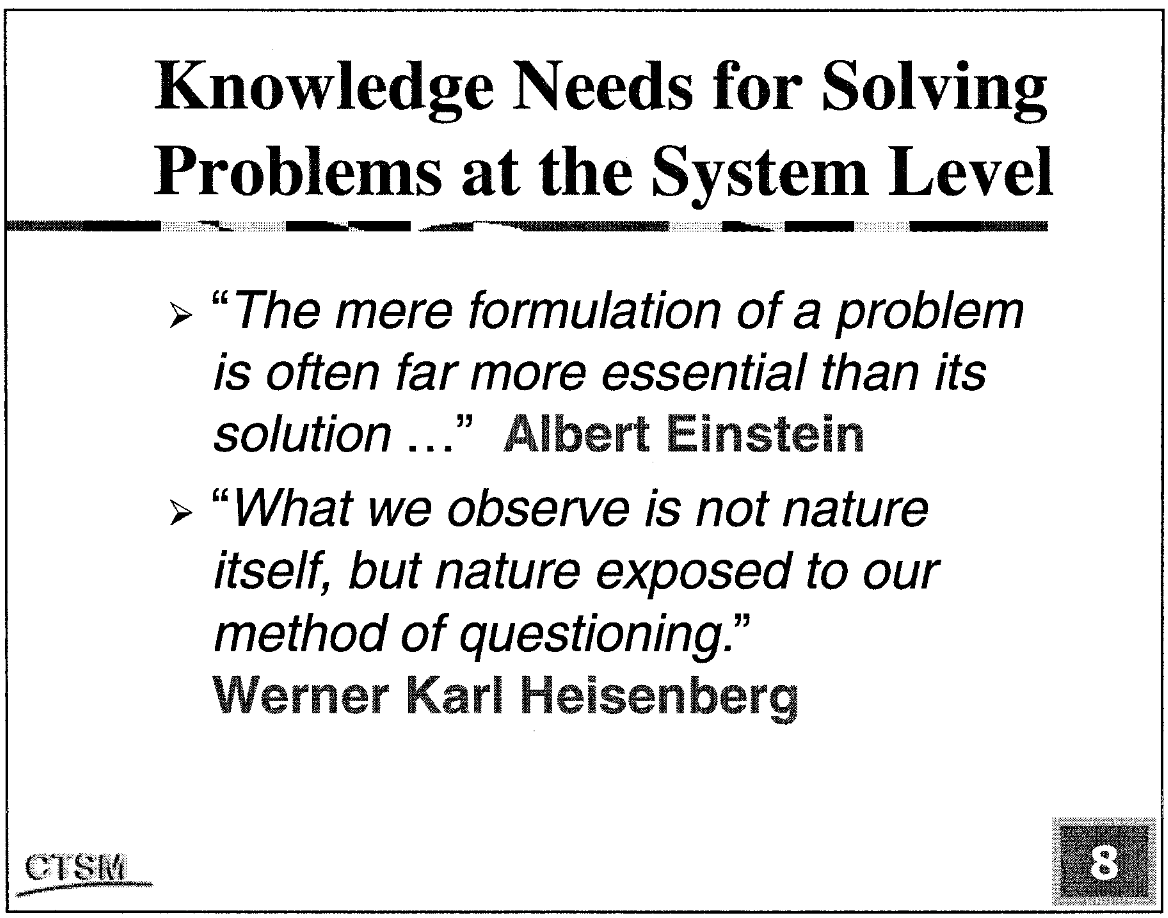


Figure 7

KNOWLEDGE CATEGORIES

A breakdown of knowledge categories, objects of knowledge and knowledge sources are provided herein. The knowledge base about a system is a mixture of truth and fallacy.

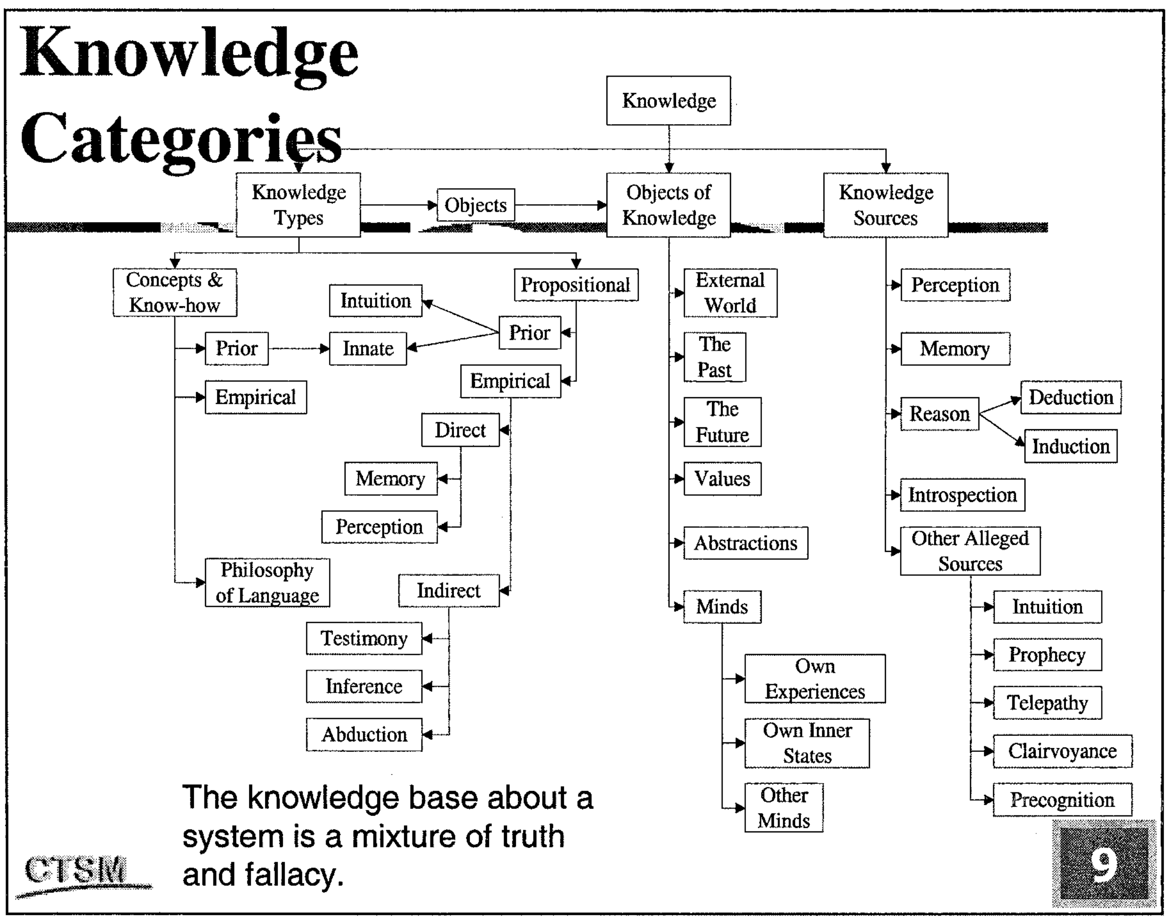


Figure 8

KNOWLEDGE, INFORMATION, OPINIONS, AND EVOLUTIONARY EPISTEMOLOGY

The definition of knowledge, information, opinions, and evolutionary epistemology are provided.

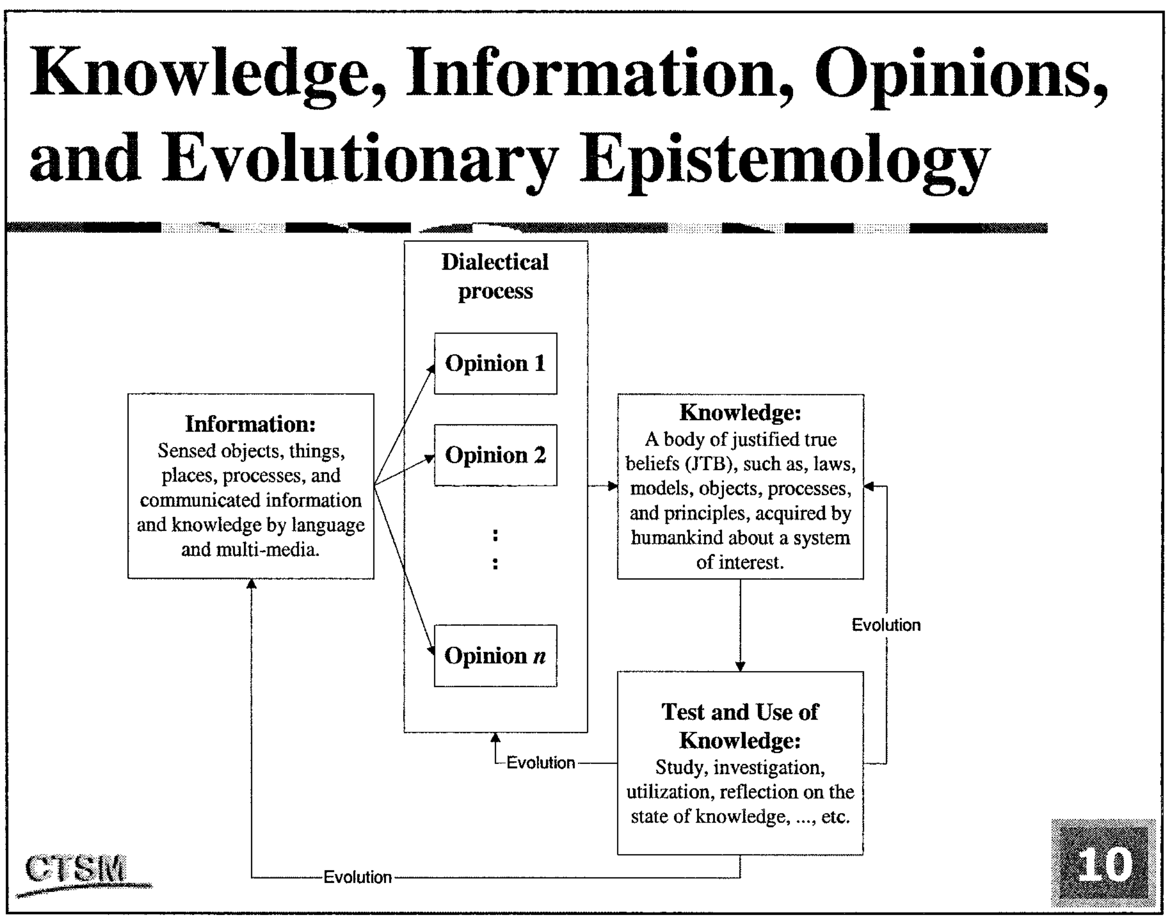


Figure 9

KNOWLEDGE DEFINITION AND CHARACTERISTICS

Knowledge is defined and its characteristics are provided. Knowledge is relative with potential biasedness and time asymmetry.

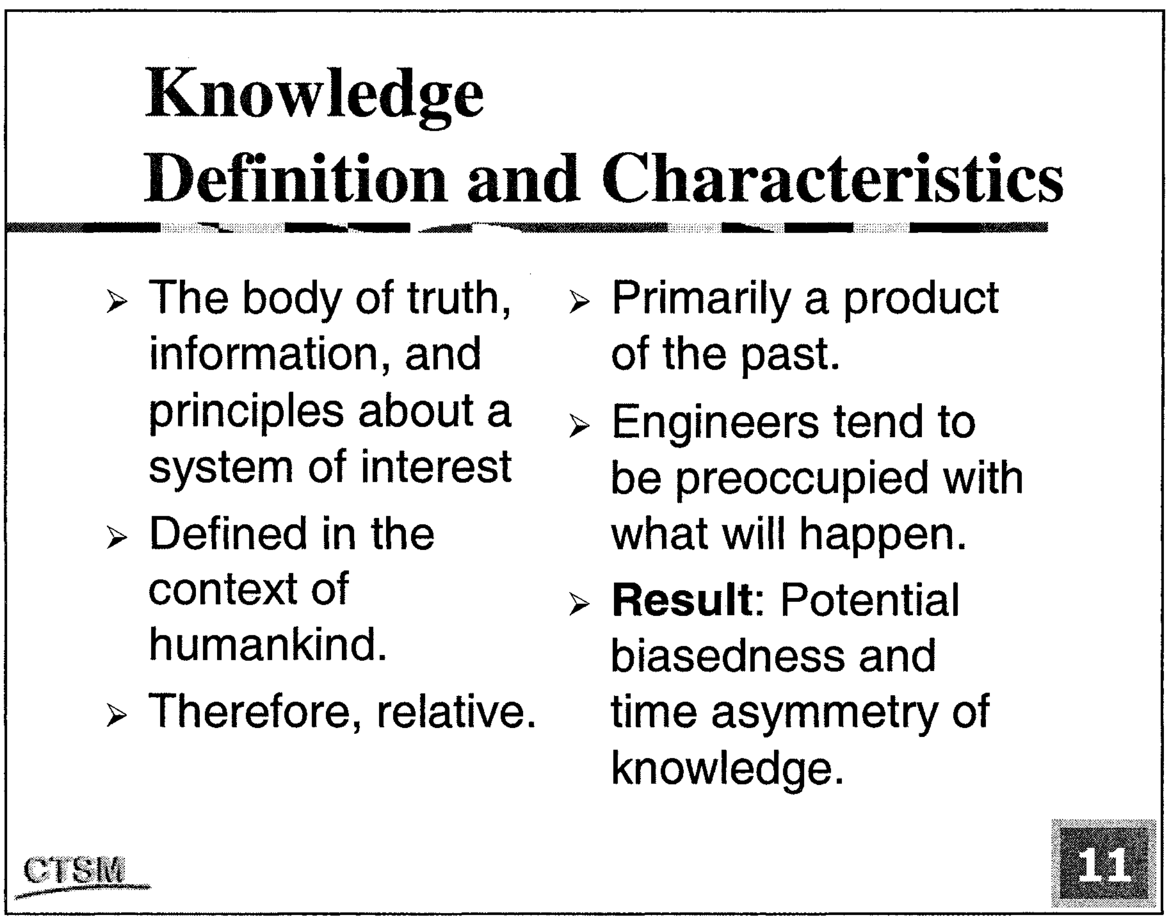


Figure 10

CLASSIFICATION OF IGNORANCE

Ignorance can be classified into three groups with a subsequent level of blind ignorance and conscious ignorance. The state of ignorance for a person or society can be unintentional or deliberate due to an erroneous cognition state and not knowing relevant information, or ignoring information and deliberate inattention to something for various reasons such as limited resources or cultural opposition, respectively. The latter type is a state of conscious ignorance which is not intentional, and once recognized evolutionary species try to correct for that state for survival reasons with varying levels of success. The former ignorance type belongs to the blind ignorance category. Therefore, ignoring means that someone can either unconsciously or deliberately refuse to acknowledge or regard, or leave out an account or consideration for relevant information (di Carlo 1998). These two states should be treated in developing a hierarchal breakdown of ignorance.

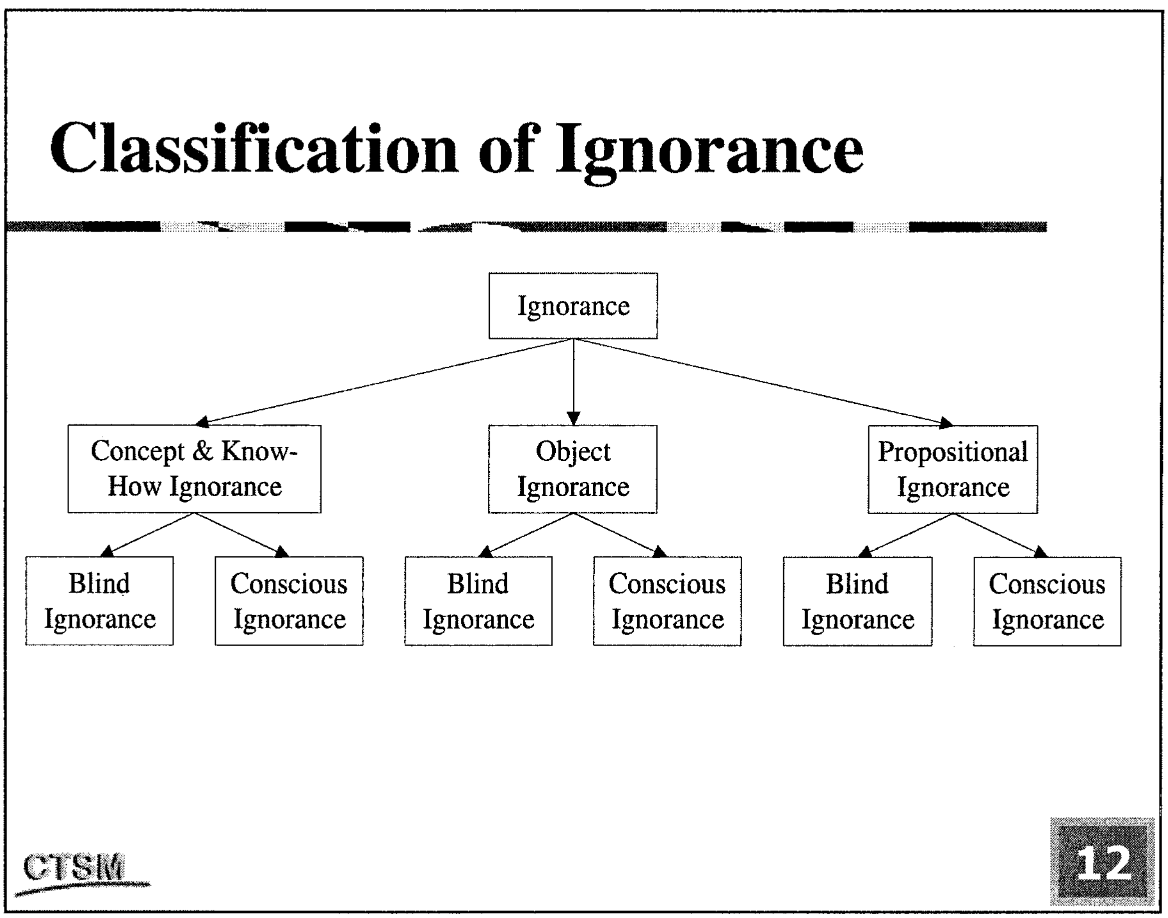


Figure 11

CLASSIFICATION OF IGNORANCE

Ignorance can be viewed to have a hierarchal classification based on its sources and nature as shown in the figure. Ignorance can be classified into two types, blind ignorance (also called meta-ignorance), and conscious ignorance (also called reflective ignorance).

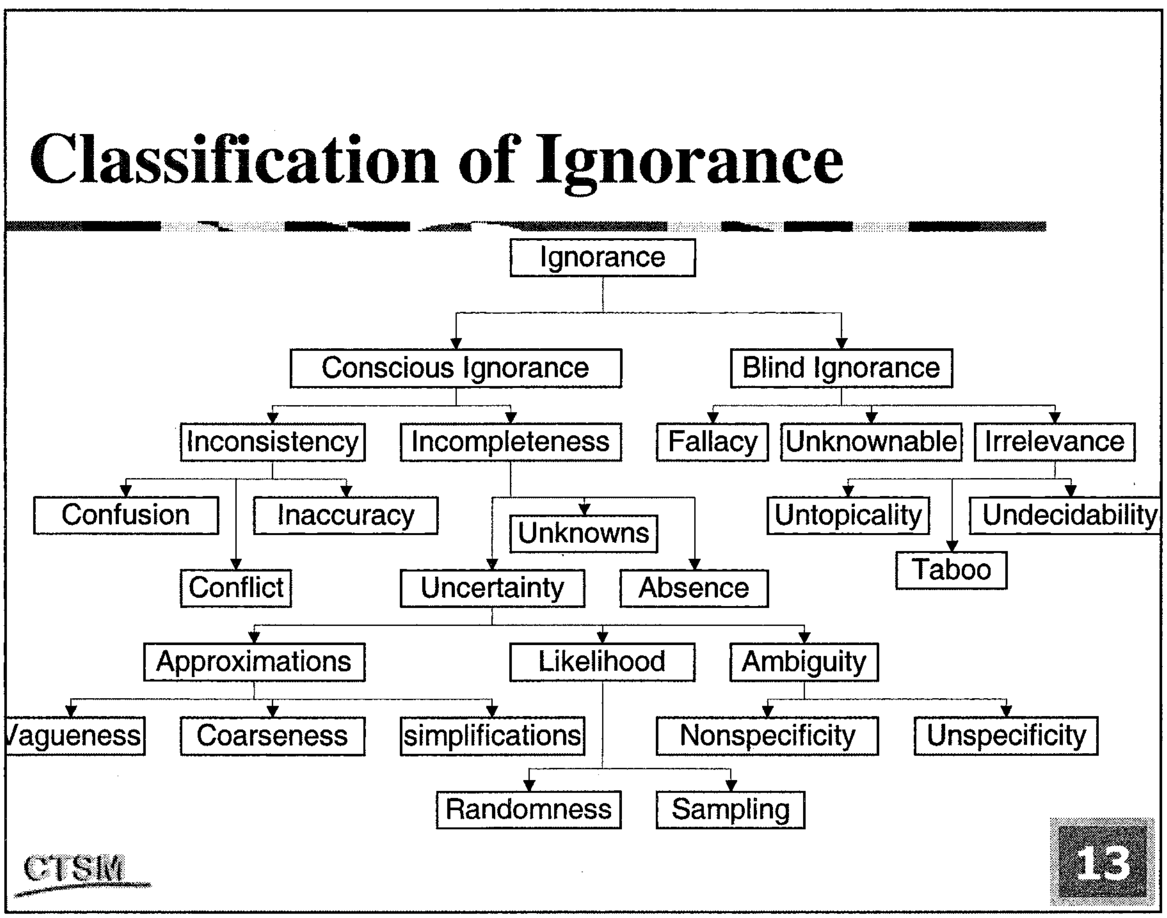


Figure 12

BLIND IGNORANCE

Blind ignorance includes not knowing relevant know-how, objects-related information, and relevant propositions that can be justified. The unknowable knowledge can be defined as knowledge that cannot be attained by humans based on current evolutionary progressions, or cannot be attained at all due to human limitations, or can only be attained through quantum leaps by humans. Blind ignorance also includes irrelevant knowledge that can be of two types: (1) relevant knowledge that is dismissed as irrelevant or ignored, and (2) irrelevant knowledge that is believed to be relevant through non-reliable or weak justification or as a result of ignoratio elenchi. The irrelevance type can be due to untopicality, taboo, and undecidability. Untopicality can be attributed to intuitions of experts that could not be negotiated with others in terms of cognitive relevance. Taboo is due to socially reinforced irrelevance. Issues that people must not know, deal with, inquire about, or investigate define the domain of taboo. The undecidability type deals with issues that cannot be designated true or false because they are considered insoluble, or solutions that are not verifiable, or as a result of ignoratio elenchi. A third component of blind ignorance is fallacy that can be defined as erroneous beliefs due to misleading notions.

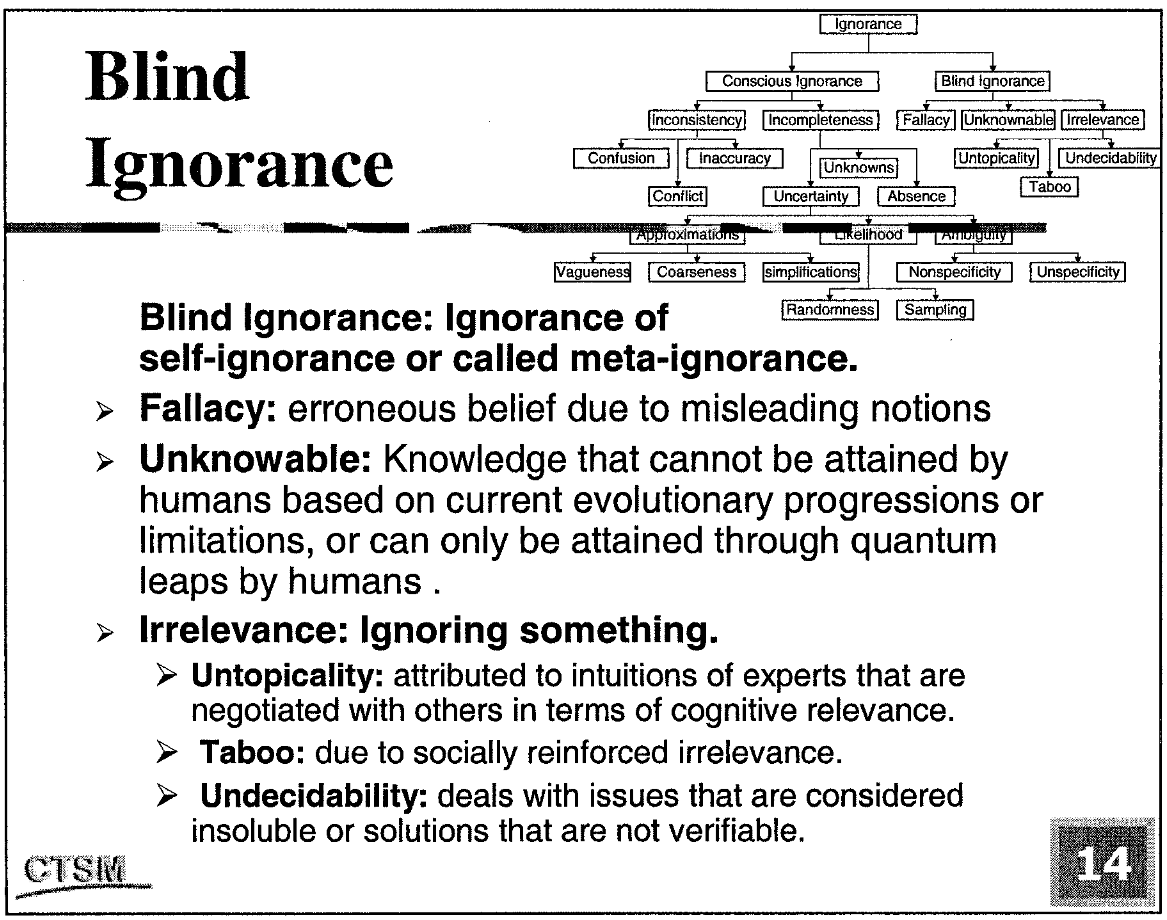


Figure 13

CONSCIOUS IGNORANCE

It has two primary components of inconsistency and incompleteness as detailed in the figure.

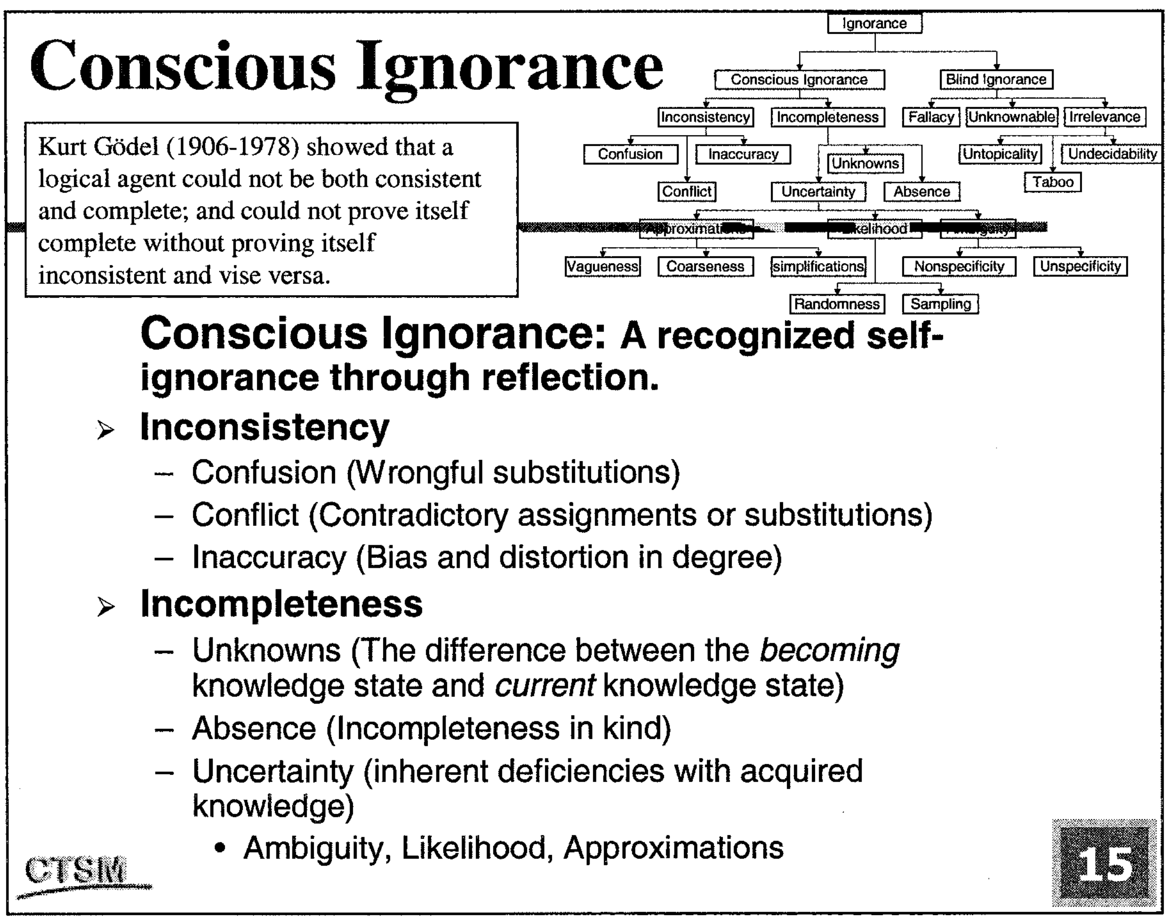
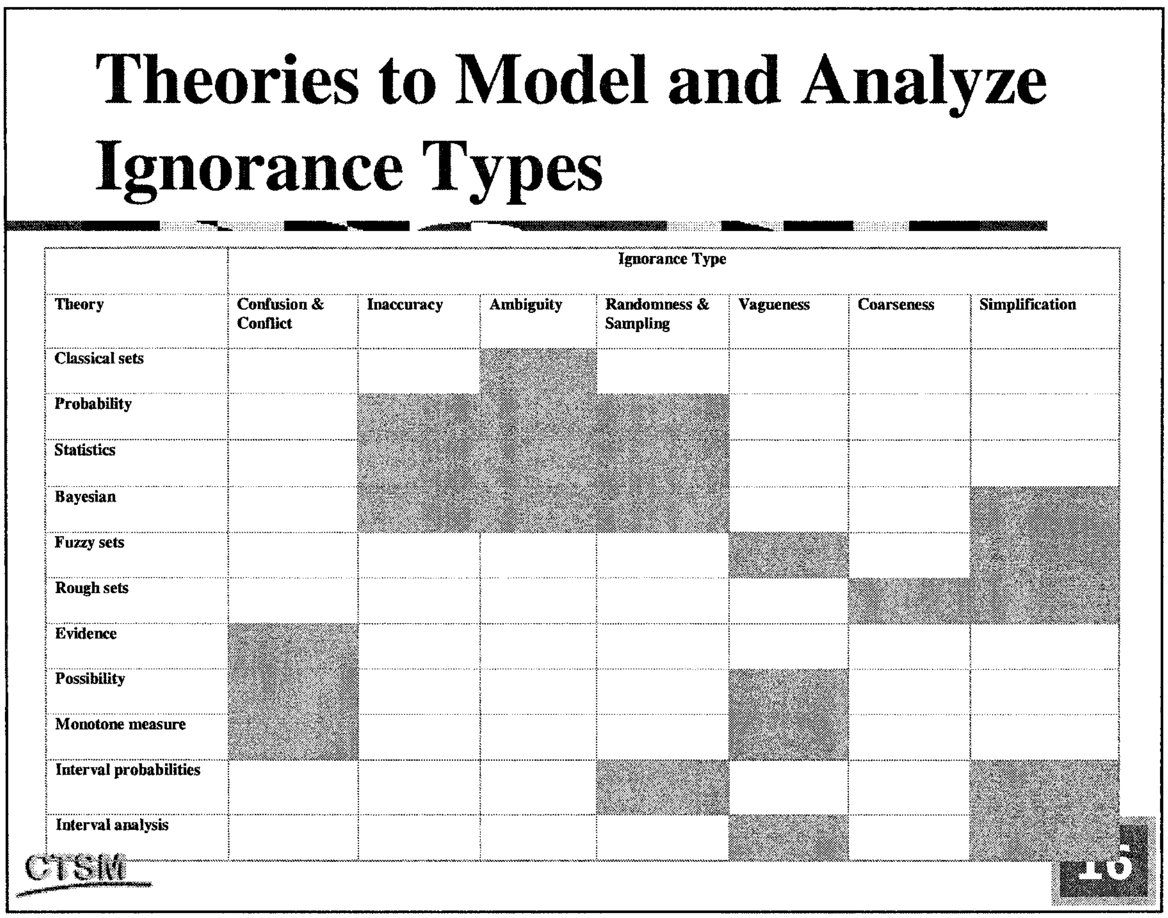


Figure 14

THEORIES TO MODEL AND ANALYZE IGNORANCE TYPES

This table maps available theories to various ignorance categories. Ayyub (2001) provides details on this classification and theories recommended for various categories.


Theories to Model and Analyze Ignorance Types

	Ignorance Type						
Theory	Confusion & Conflict	Inaccuracy	Ambiguity	Randomness & Sampling	Vagueness	Coarseness	Simplification
Classical sets							
Probability							
Statistics							
Bayesian							
Fuzzy sets							
Rough sets							
Evidence							
Possibility							
Monotone measure							
Interval probabilities							
Interval analysis							

Figure 15

SYSTEM DEFINITION LIMITATIONS

Two limitations are provided that correspond to organized and non-structured complexity. Ayyub (2001) discusses and demonstrates these limitations.

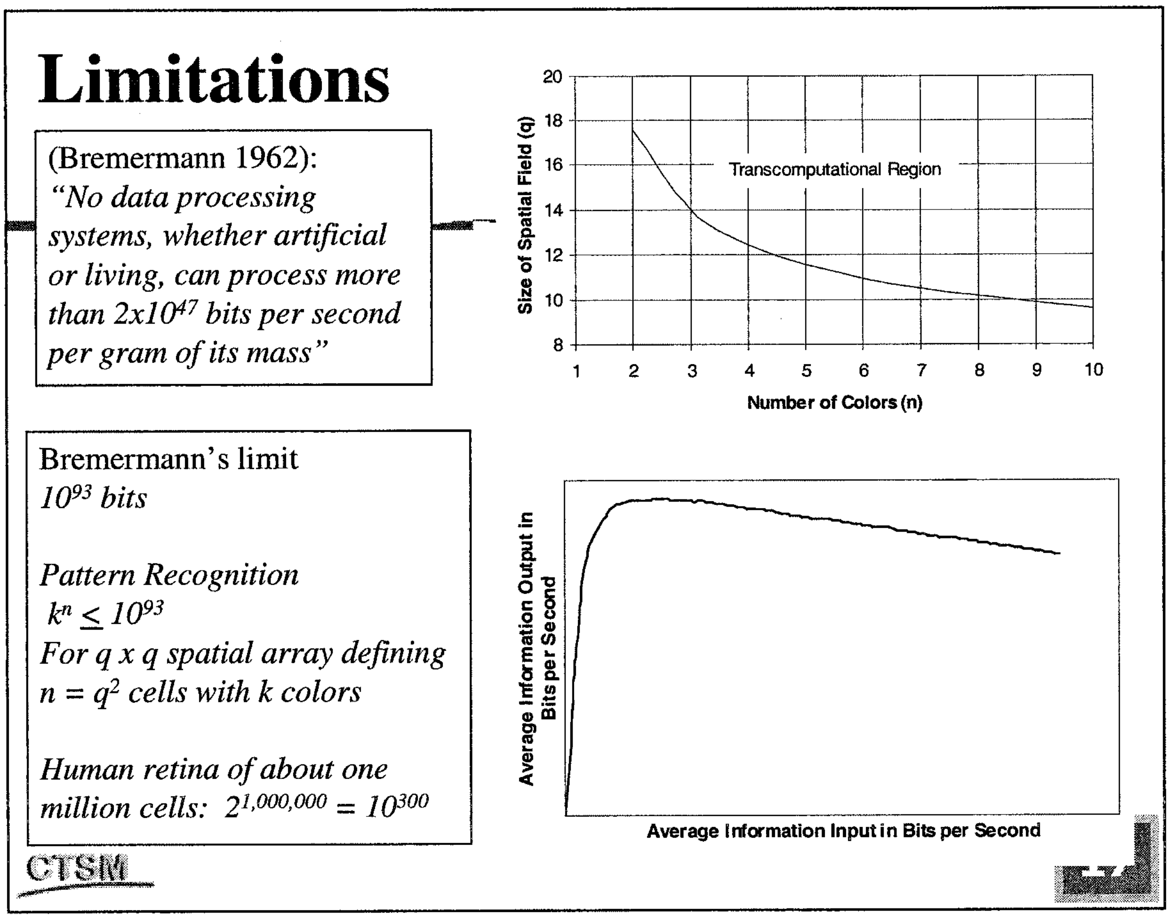


Figure 16

SELECTED METHODS

These selected methods were described at the workshop with examples.

Selected Methods

- Probability
  - ✓ Classical theory
  - ✓ Interval probabilities
  - ✓ Imprecise probabilities
- Bayesian methods
- Fuzzy sets, fuzzy arithmetic, constrained fuzzy arithmetic, fuzzy probabilities
- Rough sets
- Possibility theory
- Fuzzy measure theory
- Dempster-Shafer theory of evidence

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Figure 17

MONOTONE MEASURES

Monotone measures provides a generalization of many methods listed in the previous viewgraph.

Monotone Measures

A *monotone measure* for a non-empty family A of subsets for a given universal set X, is a mapping as follows:

$$f\colon A \rightarrow [0,\infty]$$

For any pair A_1 and $A_2 \in A$ such that $A_1 \cap A_2 = \varnothing$, super-additive (*cooperative action* or *synergy* between A_1 and A_2):

$$f(A_1 \cup A_2) > f(A_1) + f(A_2)$$

Additive (no interaction)

$$f(A_1 \cup A_2) = f(A_1) + f(A_2)$$

Sub-additive (*inhibitory effect* or *incompatibility*)

$$f(A_1 \cup A_2) < f(A_1) + f(A_2)$$

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Figure 18

CLASSIFYING MONOTONE MEASURES

The relationships between monotone measures and selected theories are listed herein. Ayyub (2001) provides details on these relationships.

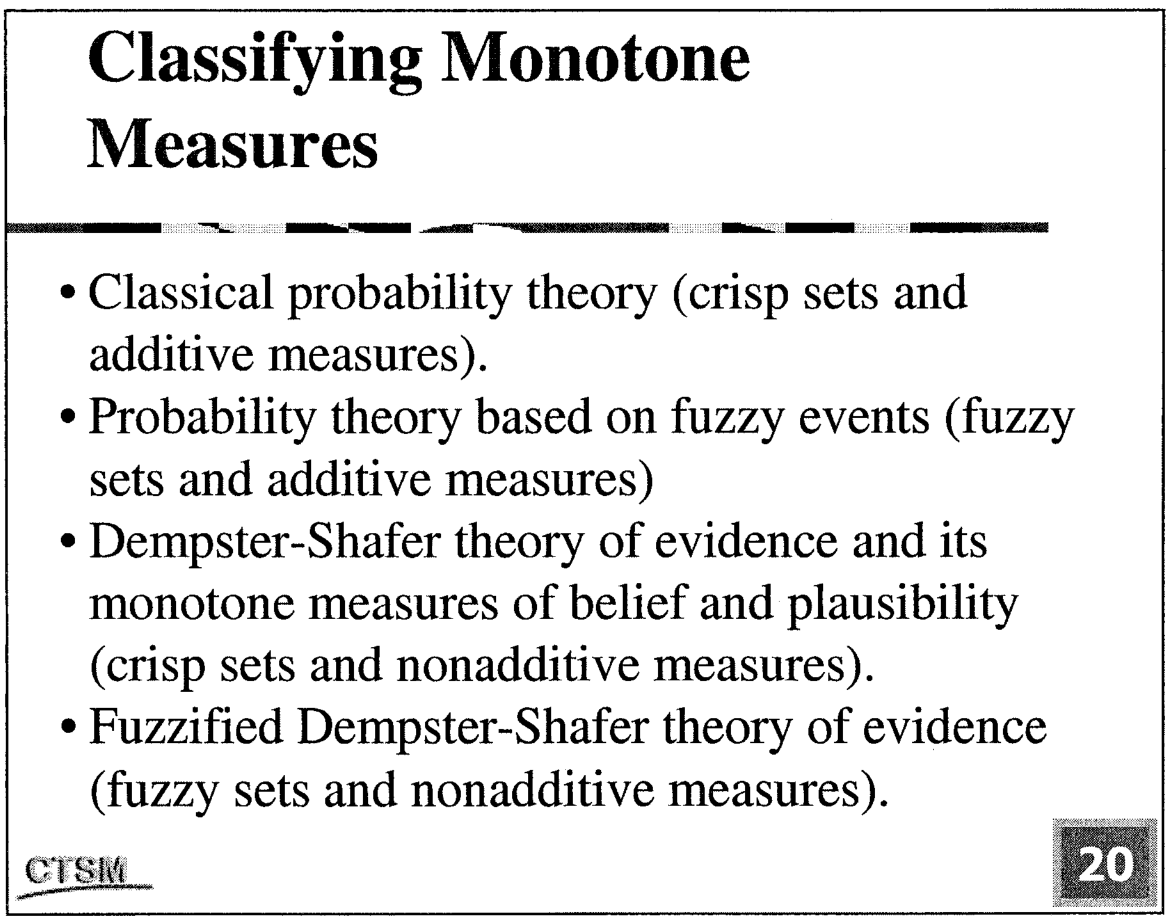

Figure 19

The relationships between monotone measures and selected theories are listed herein. Ayyub (2001) provides details on these relationships.

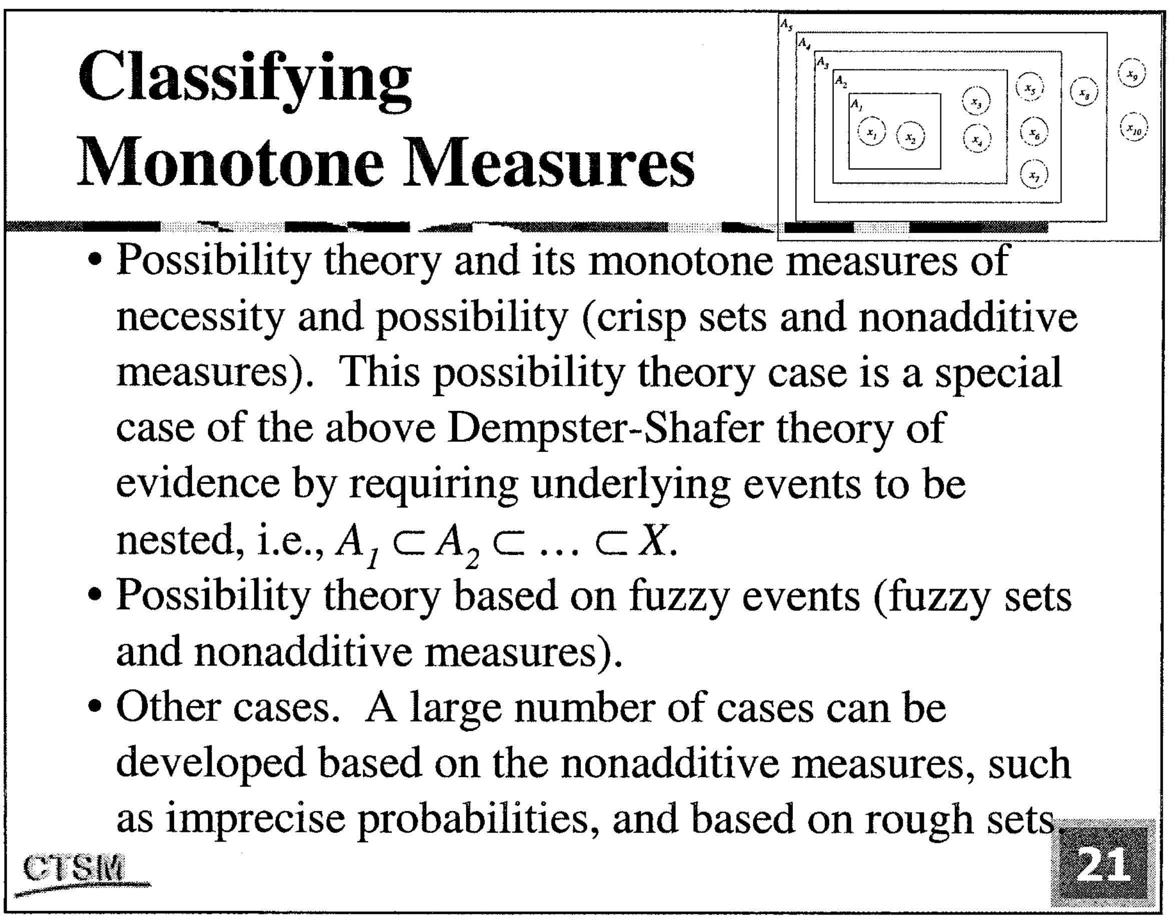

Figure 20

UNCERTAINTY-BASED INFORMATION: UNCERTAINTY MEASURES

Uncertainty measures can be used to solve engineering problems, such as regression based on minimizing uncertainty, combining expert opinions based on maximizing uncertainty, and information consolidation based on the uncertainty invariance principle.

Uncertainty-based Information : Uncertainty Measures

Uncertainty Theory	Uncertainty Measure	Equation	Uncertainty Type	Year
Classical set theory	$U(A) = \log_2 \lvert A \rvert$	(9.1)	Nonspecificity	1928
Fuzzy set theory	$U(A) = \frac{1}{h(A)} \int_0^{h(A)} \log_2 \lvert {}^{\alpha}A \rvert d\alpha$	(9.22)	Nonspecificity	1983
Possibility theory	$U(r) = \sum_{i=2}^{n} r_i \log_2 \frac{i}{i-1}$	(9.26)	Nonspecificity	1983
Evidence theory	$N(m) = \sum_{A \in \mathcal{F}} m(A) \log_2 \lvert A \rvert$	(9.36)	Nonspecificity	1985
Probability theory	$H(m) = -\sum_{x \in X} m(\{x\}) \log_2 m(\{x\})$	(9.37)	Strife	1948
Evidence theory	$S(m) = -\sum_{A \in \mathcal{F}} m(A) \log_2 \sum_{B \in \mathcal{F}} m(B) \frac{\lvert A \cap B \rvert}{\lvert A \rvert}$	(9.54)	Strife	1992
Possibility theory	$S(r) = \sum_{i=2}^{n} (r_i - r_{i+1}) \log_2 \frac{i}{\sum_{j=1}^{i} r_j}$	(9.58)	Strife	1992
Evidence theory	$NS(m) = \sum_{A \in \mathcal{F}} m(A) \log_2 \frac{\lvert A \rvert^2}{\sum_{B \in \mathcal{F}} m(B) \lvert A \cap B \rvert}$	(9.59)	Total: $N(m) + S(m)$	1992
Possibility theory	$NS(r) = \sum_{i=2}^{n} (r_i - r_{i+1}) \log_2 \frac{i^2}{\sum_{j=1}^{i} r_j}$	(9.60)	Total: $N(r) + S(r)$	1992
Fuzzy set theory	$f(A) = \sum_{x \in X} [1 - \lvert 2A(x) - 1 \rvert]$	(9.34)	Fuzziness	1979
Fuzzified evidence theory	$F(m) = \sum_{A \in \mathcal{F}} m(A) f(A)$	(9.61)	Fuzziness	1988

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Figure 21

EXPERT OPINION ELICITATION

The process of expert opinion elicitation can be used to deal with uncertainty and risk in cases were data and experiences are absent.

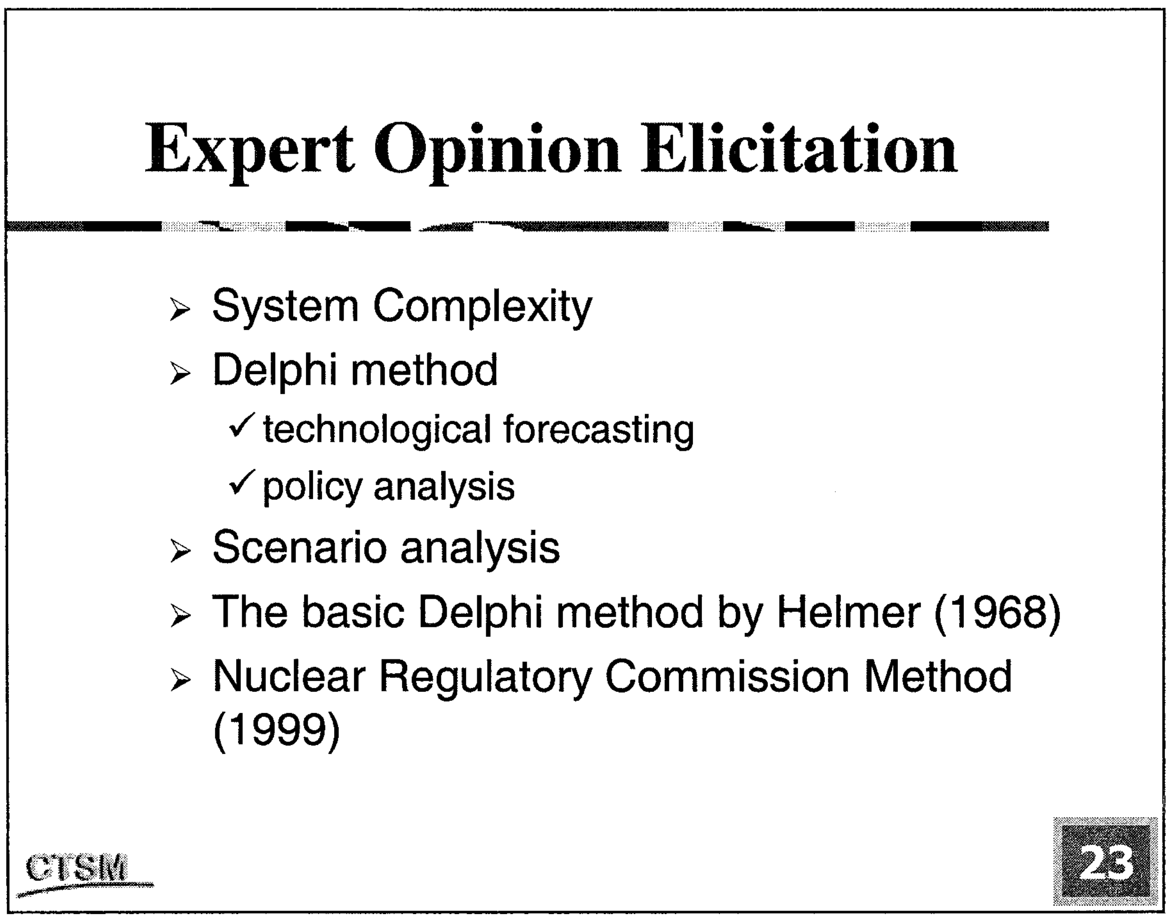

Figure 22

EXPERT OPINION ELICITATION

The process of expert opinion elicitation is described in steps.

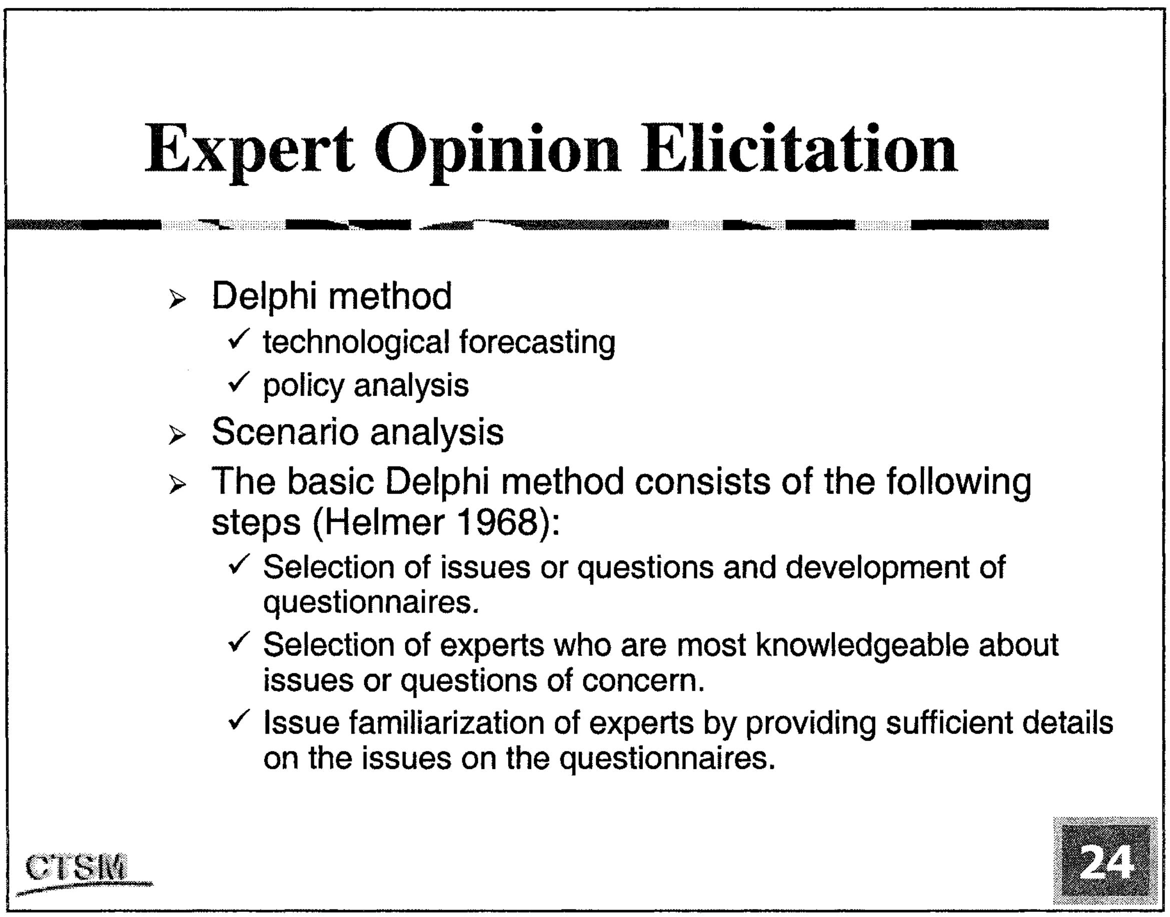

Figure 23

EXPERT OPINION ELICITATION

The process of expert opinion elicitation is described in steps.

Expert Opinion

- The basic Delphi method (Cont.):
  - ✓ Elicitation of experts about the issues. The experts generally do not know who the other respondents are.
  - ✓ Aggregation and presentation of results in the form of median values and an inter-quartile range (i.e., 25% and 75% percentile values).
  - ✓ Review of results by the experts and revision of initial answers by experts. Respondents who provide answers outside the inter-quartile range need to provide written justifications or arguments on the second cycle of completing the questionnaires.
  - ✓ Revision of results and re-review for another cycle. The process should be repeated until a complete consensus is achieved. Typically, the Delphi method requires two or three cycles or iterations.
  - ✓ A summary of the results is prepared with argument summary for out of inter-quartile range values.

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Figure 24

EXPERT OPINION ELICITATION

The process of expert opinion elicitation is described in a flowchart.

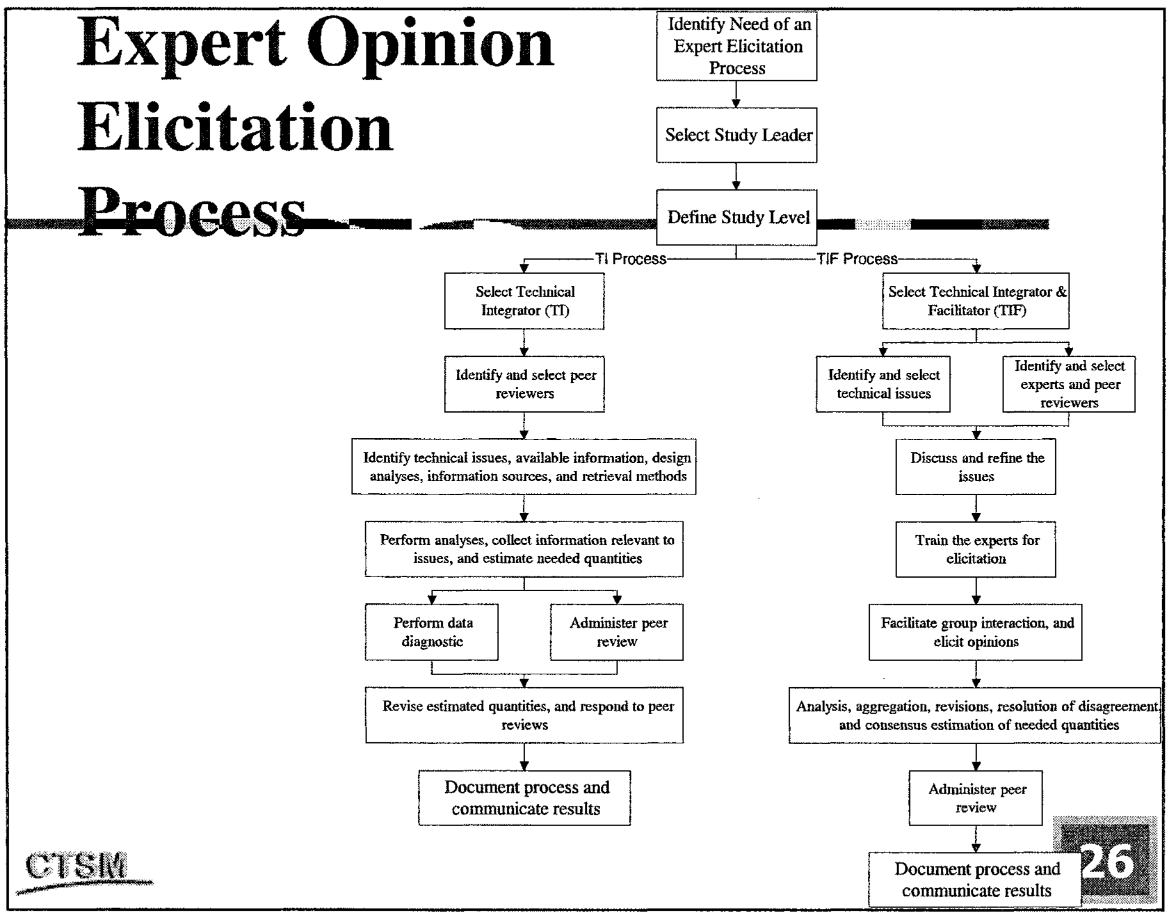

Figure 25

EXPERT OPINION ELICITATION

The outcomes of expert opinion elicitation is described including consensus and no consensus.

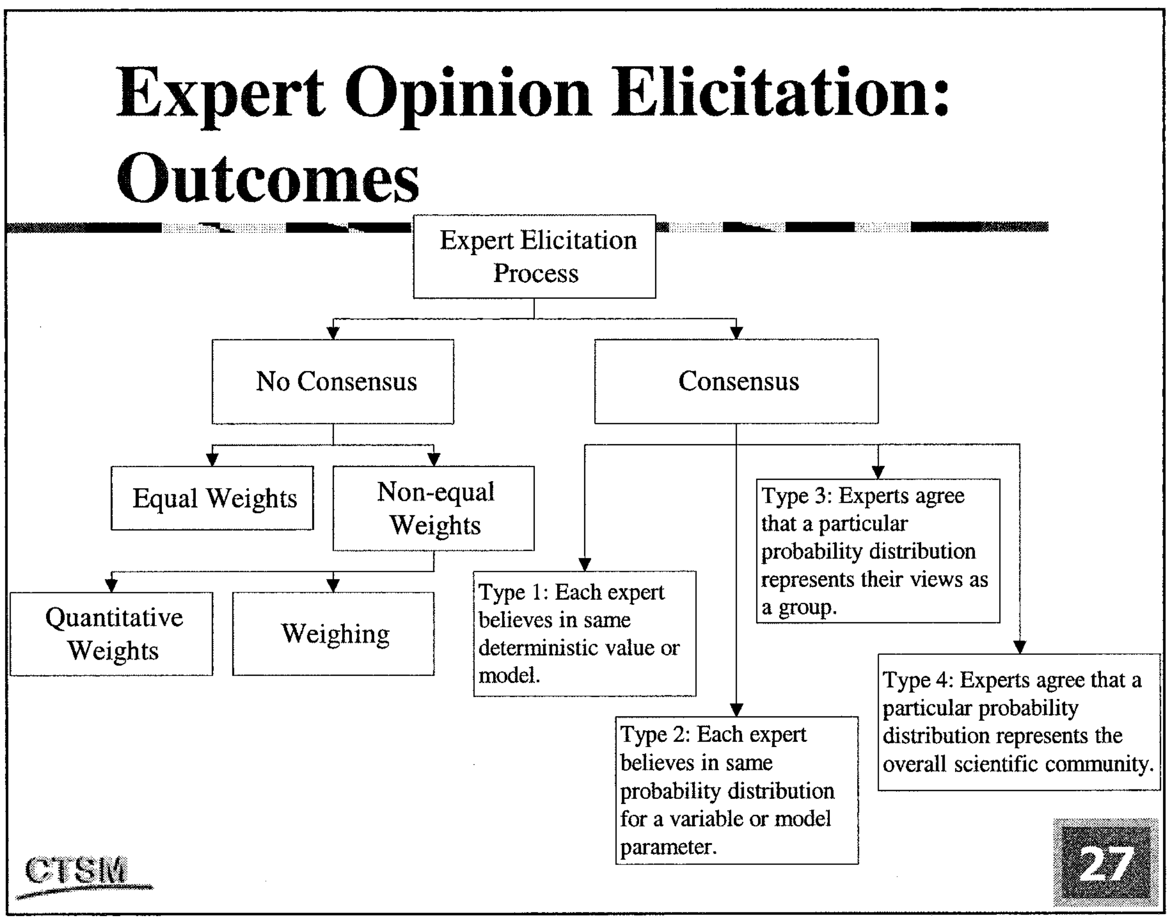

Figure 26

SUMMARY AND CONCLUDING REMARKS

A Hierarchy for ignorance is provided in this paper, and analytical methods are identified for modeling various types. Novel analytical methods and algorithms to accurately assess and model information content by classifying, analyzing and modeling ignorance types for the purpose of constructing knowledge are outlined in the paper. As our reliance on computational methods in simulation-based approaches for discovery and design, the need for formal methods to analyze and model ignorance and uncertainty is expected to increase. These methods can be used within a framework of decision analysis to meet the needs of decision and policy makers.

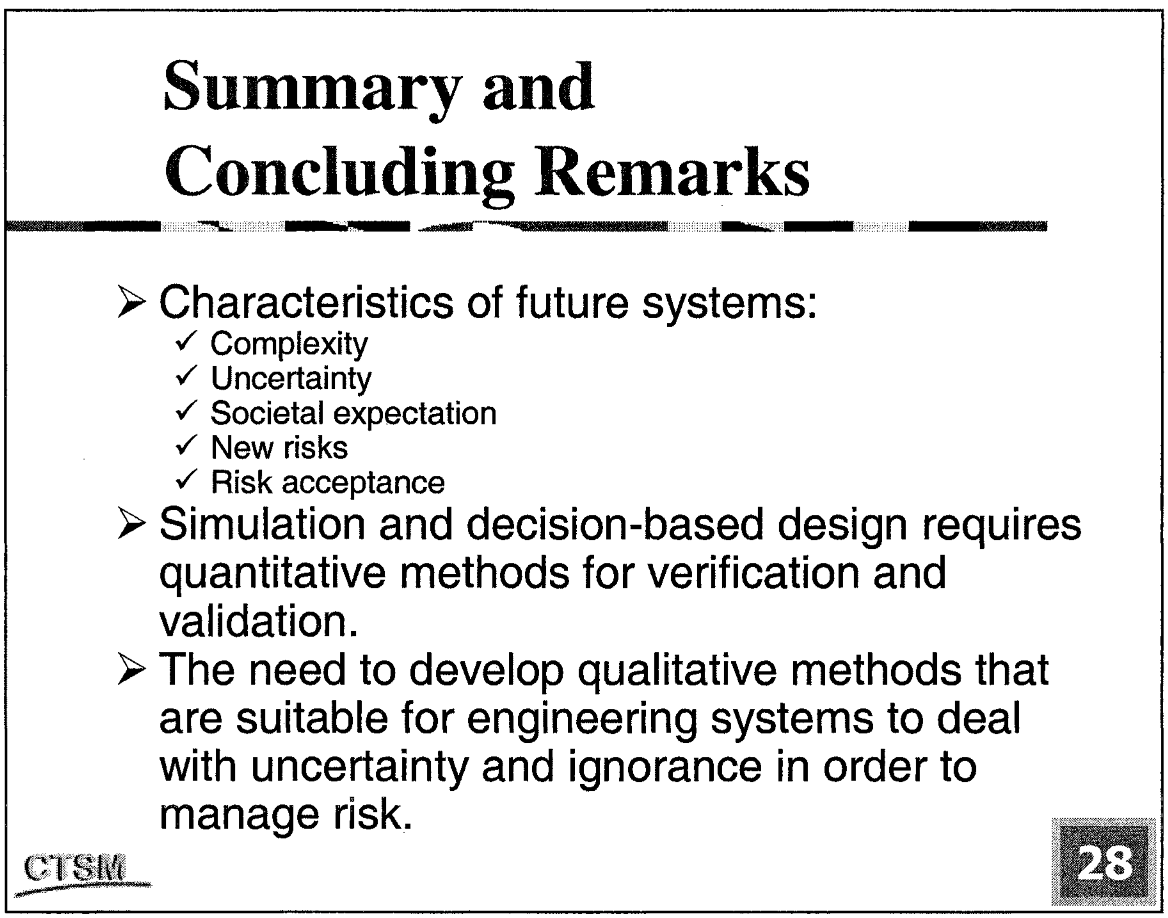

Figure 27

ADDITIONAL REFERENCES

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2. di Carlo, C. W., 1998. Evolutionary Epistemology and the Concept of Ignorance, PhD thesis, University of Waterloo, Ontario, Canada.
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7. Weinstein, D., and Weinstein, M. A., 1978. "The Sociology of Non-knowledge: a Paradigm." In R. A. Jones (Ed.) Research in the Sociology of Knowledge, Science and Art, Volume 1, JAI Press, NY.

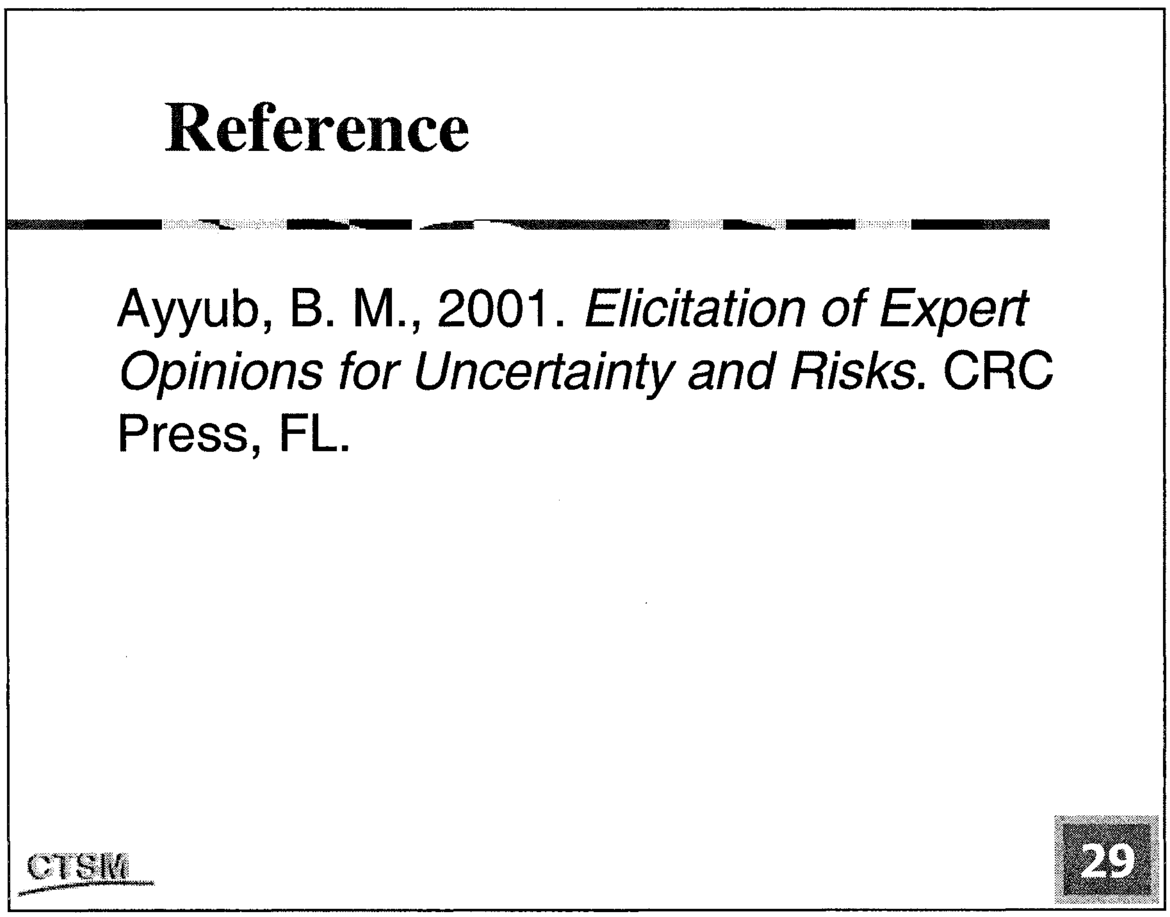

Figure 28

Methodology for the Estimation of Uncertainty and Error in Computational Simulation

Dr. William L. Oberkampf
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Albuquerque, NM 87185-0828

OUTLINE OF THE PRESENTATION

The following references describe in more detail the material given in this presentation. These references are available from the appropriate sources or can be obtained from William Oberkampf: wloberk@sandia.gov.

1. Oberkampf, W. L., Diegert, K. V., Alvin, K. F., and Rutherford, B. M., "Variability, Uncertainty, and Error in Computational Simulations," ASME-HTD-Vol. 357-2, AIAA/ASME Joint Thermophysics and Heat Transfer Conference, Albuquerque, NM, 1998.
2. Oberkampf, W. L., DeLand, S. M., Rutherford, B. M., Diegert, K. V., and Alvin, K. F., "A New Methodology for the Estimation of Total Uncertainty in Computational Simulation," American Institute of Aeronautics and Astronautics, AIAA Paper No. 99-1612, AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference and Exhibit, St. Louis, MO, 1999.
3. Oberkampf, W. L., DeLand, S. M., Rutherford, B. M., Diegert, K. V., and Alvin, K. F., "Estimation of Total Uncertainty in Modeling and Simulation," Sandia National Laboratories Report, SAND2000-0515, Albuquerque, NM, March 2000.
4. Oberkampf, W. L., Helton, J. C., and Sentz, K. "Mathematical Representation of Uncertainty," American Institute of Aeronautics and Astronautics, AIAA Paper No. 2001-1645, AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference and Exhibit, Seattle, WA, 2001.

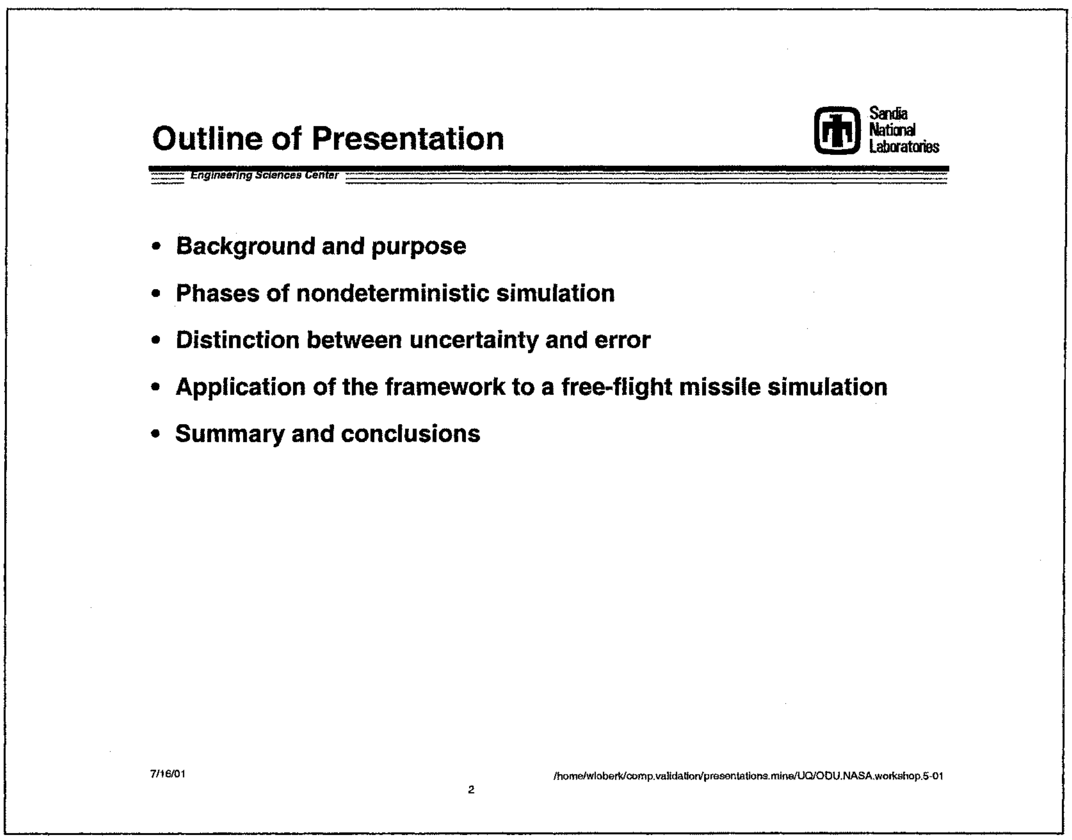

Figure 1

BACKGROUND AND PURPOSE

Our focus is on developing a framework for identifying and estimating error and uncertainty in nondeterministic computational simulation. This framework is composed of six phases, which represent a synthesis of the activities recognized in the systems engineering (operations research) community, the probabilistic risk assessment community, and the numerical methods community. Our framework emphasizes models that are given by a set of partial differential equations (PDEs) that must be solved numerically, although the framework is also applicable to modeling in general. We stress a clear distinction between the specification of the system, which is modeled by a set of PDEs, and the environment, which should be representative of the boundary conditions and excitation for the PDEs. We make a distinction between error and uncertainty so that the issues of representation and propagation of each is aided. The issue of numerical solution error is generally ignored in risk assessment analyses and nondeterministic simulations. Neglecting numerical solution error can be particularly detrimental to uncertainty estimation when the mathematical models of interest are cast in terms of nonlinear PDEs. Types of numerical error that are of concern in the numerical solution of PDEs are spatial discretization error in finite element and finite difference methods, temporal discretization error in time-dependent simulations, and error due to discrete representation of strongly nonlinear interactions.

Background and Purpose

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Develop a general framework for estimating uncertainty and error in nondeterministic computational simulations

- **Scope of framework:**
  - **Continuum mechanics and energy transport**
  - **Mathematical models are given by a system of ordinary or partial differential equations**
  - **Differential equations are solved by discretization methods (finite element, finite difference, finite volume methods)**
- **Approach represents a synthesis of methods from:**
  - **Systems Engineering (nuclear reactor risk assessment)**
  - **Statistics (probabilistic structural mechanics)**
  - **Numerical solution of PDEs (finite element methods)**

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Figure 2

STEPS IN QUANTIFYING UNCERTAINTY AND ERROR IN NONDETERMINISTIC SIMULATIONS

One could identify four steps in quantifying uncertainty and error in nondeterministic simulations. First, one constructs a mathematical model of the system of interest. This model must define where the physical system ends and the environment, or surroundings, begin. Second, one must specify where and how all of the modeled uncertainties and errors appear in the formulation of the nondeterministic simulation. Third, given these uncertainties and errors, one assumes a mathematical representation that will be used to describe these uncertainties and errors. For example, uncertainties are traditionally represented by probability distributions. Fourth, one must propagate and aggregate these mathematical representations of uncertainty and error through the nondeterministic computational process.

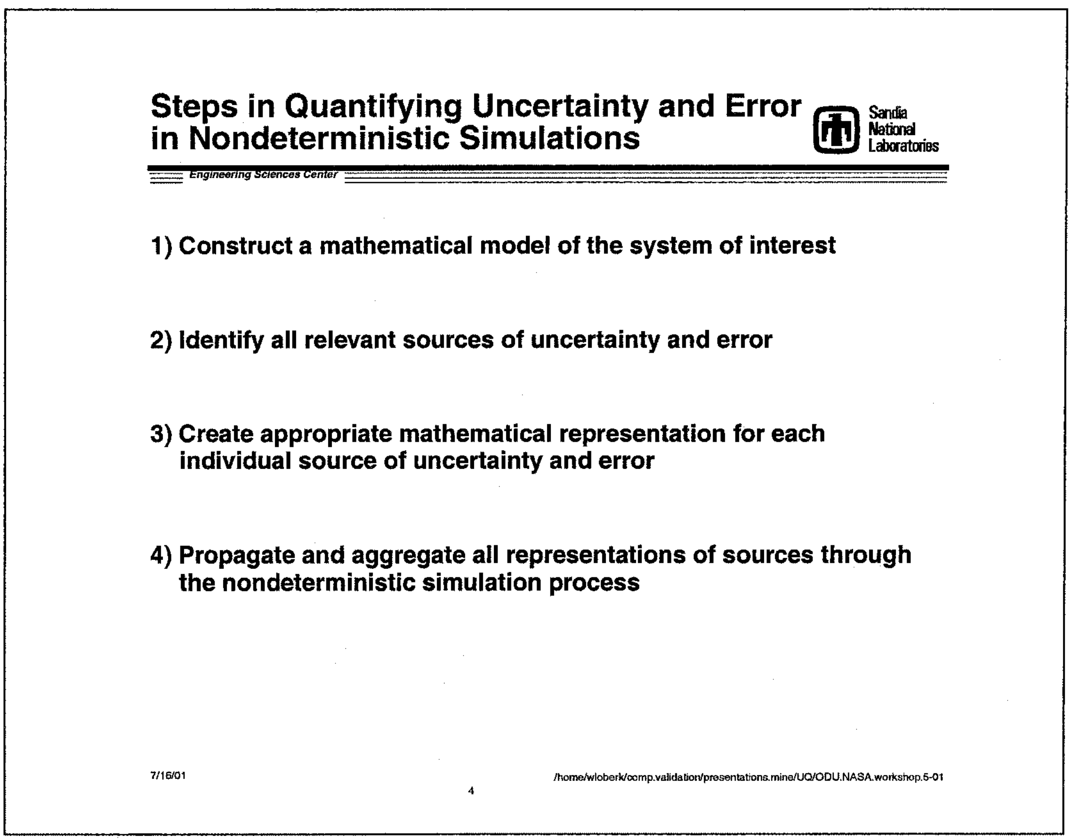

Figure 3

PHASES IN NONDETERMINISTIC SIMULATIONS

This presentation proposes a comprehensive new framework, or structure, of the general phases of modeling and simulation. The phases are, 1) conceptual modeling of the physical system, 2) mathematical modeling of the conceptual model, 3) discretization and algorithm selection for the mathematical model, 4) computer programming of the discrete model, 5) numerical solution of the computer program model, and 6) representation of the numerical solution. Characteristics and activities of each of the phases are applicable to a variety of disciplines, e.g., computational fluid dynamics, structural dynamics, and heat transfer. We also distinguish between aleatory uncertainty, epistemic uncertainty, and error that might occur in any of the phases of modeling and simulation.

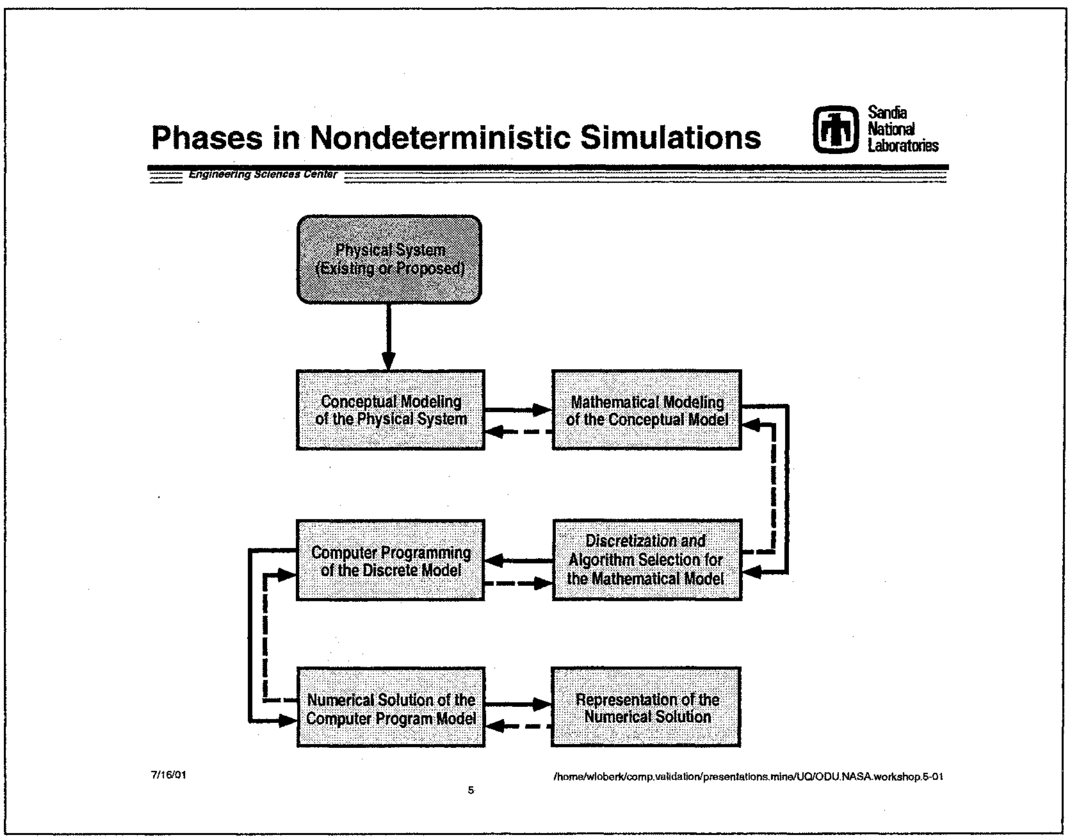

Figure 4

TYPES OF UNCERTAINTY

We use the term aleatory uncertainty to describe the inherent variation associated with the physical system or the environment under consideration. Sources of aleatory uncertainty can commonly be singled out from other contributors to nondeterministic simulation by their representation as distributed quantities that can take on values in an established or known range, but for which the exact value will vary by chance from unit to unit or from time to time. Aleatory uncertainty is also referred to in the literature as stochastic uncertainty, variability, inherent uncertainty, and irreducible uncertainty. We define epistemic uncertainty as a potential deficiency in any phase or activity of the modeling process that is due to lack of knowledge. The first feature that our definition stresses is "potential," meaning that the deficiency may or may not exist. In other words, there may be no deficiency, say in the prediction of some event, even though there is a lack of knowledge if we happen to model the phenomena correctly. The second key feature of epistemic uncertainty is that its fundamental cause is incomplete information. Incomplete information can be caused by vagueness, non-specificity, or dissonance. Epistemic uncertainty is also referred to as reducible uncertainty and ignorance.

Types of Uncertainty

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Aleatory uncertainty is the *inherent* variation associated with the physical system or the environment.

- **Also referred to as irreducible uncertainty, variability, and stochastic uncertainty.**

- **Examples:**
  - **Variation in thermodynamic properties due to manufacturing**
  - **Variation in joint stiffness and damping in structures**
  - **Variation in external excitation of a system**

Epistemic uncertainty is a potential deficiency in any phase of the modeling process that is due to *lack of knowledge*.

- **Also referred to reducible uncertainty, model form uncertainty, and subjective uncertainty.**

- **Examples:**
  - **Poor understanding of fracture dynamics**
  - **Poor knowledge of failure, misuse, or hostile scenarios**
  - **Information from expert-opinion elicitation**

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Figure 5

ERROR IN COMPUTATIONAL SIMULATIONS

We define error as a recognizable deficiency in any phase or activity of modeling and simulation that is not due to lack of knowledge. Our definition stresses the feature that the deficiency is identifiable or knowable upon examination; that is, the deficiency is not caused by lack of knowledge. Essentially there is an agreed-upon approach or ideal condition that is considered to be more accurate. If divergence from the correct or more accurate approach is pointed out, the divergence is either corrected or allowed to remain. It may be allowed to remain because of practical constraints, such as the error is acceptable given the requirements, or the cost to correct it is excessive. This implies a segregation of error types: an error can be either acknowledged or unacknowledged. Acknowledged errors are those deficiencies that are recognized by the analysts. When acknowledged errors are introduced by the analyst into the modeling or simulation process, the analyst typically has some idea of the magnitude or impact of such errors. Examples of acknowledged errors are finite precision arithmetic in a computer, approximations made to simplify the modeling of a physical process, and conversion of PDEs into discrete equations. Unacknowledged errors are those deficiencies that are not recognized by the analyst, but they are recognizable. Examples of unacknowledged errors are blunders or mistakes; that is, the analyst intended to do one thing in the modeling and simulation but, for example, as a result of human error, did another. There are no straightforward methods for estimating, bounding, or ordering the contribution of unacknowledged errors.

Error in Computation Simulations

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Error is recognizable deficiency in any phase of the modeling and simulation process that is *not* due to lack of knowledge.

- **Acknowledged errors are errors that can be estimated, bounded, or ordered**
  - **Finite precision arithmetic in a digital computer**
  - **Lack of spatial grid convergence**
  - **Conversion from continuum PDEs to discrete mathematics**
- **Unacknowledged errors are blunders or mistakes:**
  - **Programming errors**
  - **Input and output errors**
  - **Compilation and linkage errors**

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Figure 6

EXAMPLE PROBLEM: MISSILE FLIGHT ANALYSIS

In this example we consider an analysis of the flight of a rocket-boosted, aircraft-launched missile. We make the following assumptions concerning the missile:

1. The missile is unguided during its entire flight, i.e., only ballistic flight is considered.

2. The missile is propelled by a solid fuel rocket motor for the initial portion of its flight, and it is unpowered during the remainder of the flight.

3. The missile is fired from a launch rail attached to the aircraft in flight.

4. The only aerodynamic surfaces on the missile are fins to provide flight stability.

The analysis considers the missile flight to be in the unspecified future, i.e., the analysis is an attempt to predict future plausible events, not analyze an event in the past. The analysis requires the estimated uncertainty in all of the plausible events.

Example Problem:
Missile Flight Analysis

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- **Problem description:**
    - **Rocket-boosted, aircraft-launched missile**
    - **Unguided during entire flight**
    - **Propelled by a solid fuel rocket motor**
    - **Fired from a launch rail on the aircraft**
- **Typical purposes of nondeterministic analyses:**
    - **1) Missile performance (normal environments)**
    - **2) Flight safety (abnormal environments)**
    - **3) Missile reliability (hostile environments)**

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Figure 7

PHASES OF NONDETERMINISTIC SIMULATIONS

We have identified four major activities that are conducted in the conceptual modeling phase: system/environment specification, scenario abstraction, coupled physics specification, and nondeterministic specification. The system/environment-specification activity consists primarily of carefully identifying the physical or conceptual elements that are considered part of the system and those that are considered part of the environment. The scenario-abstraction activity attempts to identify all possible physical events, or sequences of events, that may affect the goals of the analysis. The coupled physics specification identifies and carefully distinguishes the possible alternatives for physical and chemical processes in the system, and the coupling between these processes for the system/environment specification and scenario abstraction under consideration. In the nondeterministic specification activity, decisions are made concerning what aspects of the system and environment will be considered deterministic or nondeterministic.

We have identified four major activities in the mathematical modeling phase: formulation of the PDEs, selection of all auxiliary equations that supplement the differential equations, formulation of all initial and boundary conditions required to solve the PDEs, and selection of the mathematical representation of nondeterministic elements of the analysis. The PDEs commonly represent conservation equations for mass, momentum, and energy, but they can originate from any mathematical model of the system. The auxiliary equations are equations that are required to complete the PDEs. The boundary and initial conditions provide the required closure equations needed for all PDEs. Formulation of the nondeterministic representations is based on the needs of the analysis, as well as the quantity and quality of relevant information available.

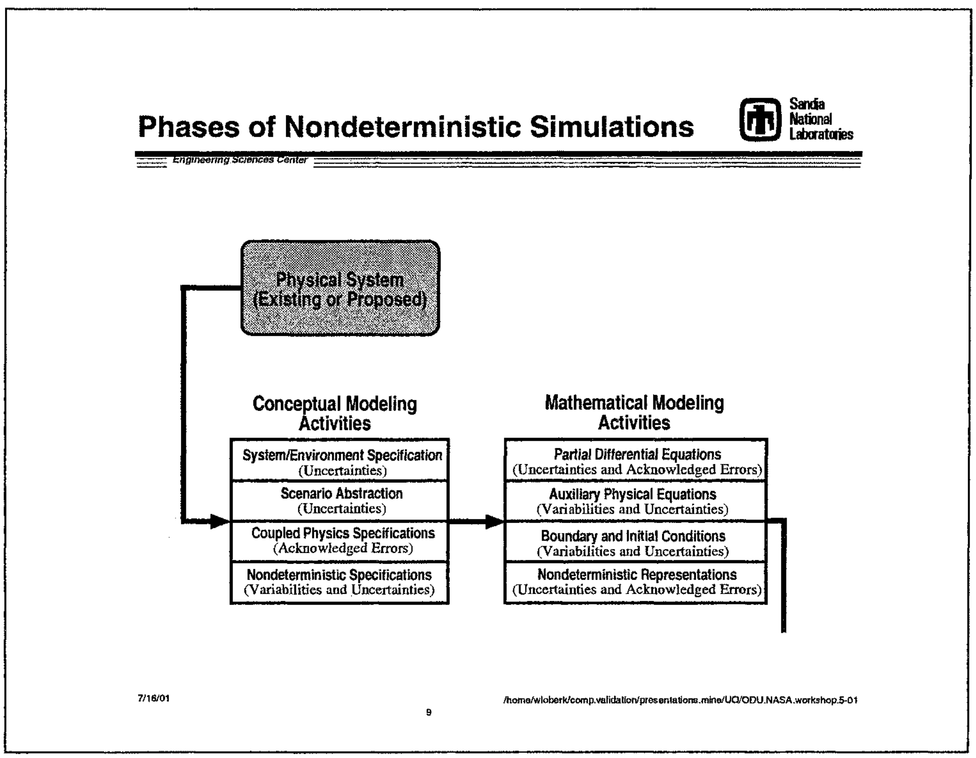

Figure 8

CONCEPTUAL MODELING ACTIVITIES

Three possible system/environment specifications for the missile flight example are shown. The specifications are listed from the most inclusive (with regard to the system specification) to the least inclusive. System/Environment Specification 1 considers the missile and the atmosphere near the missile to be part of the system, whereas the launching aircraft and target are considered part of the environment. System/Environment Specification 2 considers the missile and the aerothermal processes occurring on the missile to be part of the system, whereas the atmosphere near the missile, the launching aircraft, and the target are considered part of the environment. System/Environment Specification 3 considers the missile to be the system, whereas the aero thermal processes, atmosphere near the missile, launching aircraft, and target are considered part of the environment. Even though this is the simplest specification considered, it still allows for significant complexities in the analysis. Note that in the diagram the only specification, or tree element, delineated is System/Environment Specification 3.

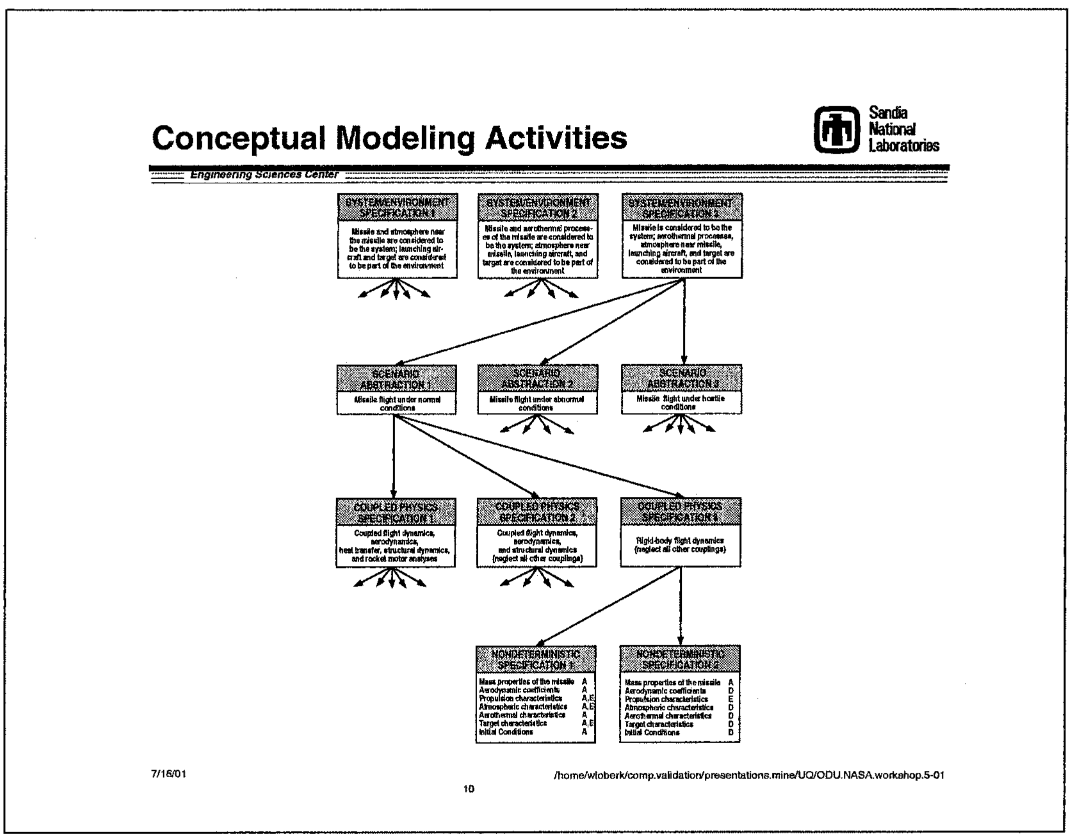

Figure 9

ACTIVITIES IN THE REMAINING PHASES OF NONDETERMINISTIC SIMULATIONS

The discretization and algorithm selection phase accomplishes two related activities. First, it converts the continuum mathematics model, i.e., the differential equations, into a discrete mathematics problem suitable for numerical solution. Second, it provides the methodology determining how a discrete set of computer solutions can be most appropriately used to accommodate the nondeterministic features of the analysis. Three activities are identified in the computer-programming phase: input preparation, module design and coding, and compilation and linkage. Input preparation refers to the analyst's conversion of the mathematical and discrete model elements into equivalent data elements usable by the application code. The second and third activities relate to the building of the application code itself. Four activities are identified in the numerical solution phase: spatial and temporal convergence, iterative convergence, nondeterministic propagation convergence, and computer round-off accumulation. In the solution representation phase we have identified five activities: input preparation, module design and coding, compilation and linkage, data representation, and data interpretation. The first three activities are very similar to those discussed in the computer-programming phase. The data representation activity includes two types of similar activities: 1) the representation of individual solutions over the independent variables of the PDEs and 2) a summary representation that combines elements of the multiple individual deterministic computer runs. The data interpretation activity refers to the human perceptions or impressions that are formed based on observation of the represented solutions.

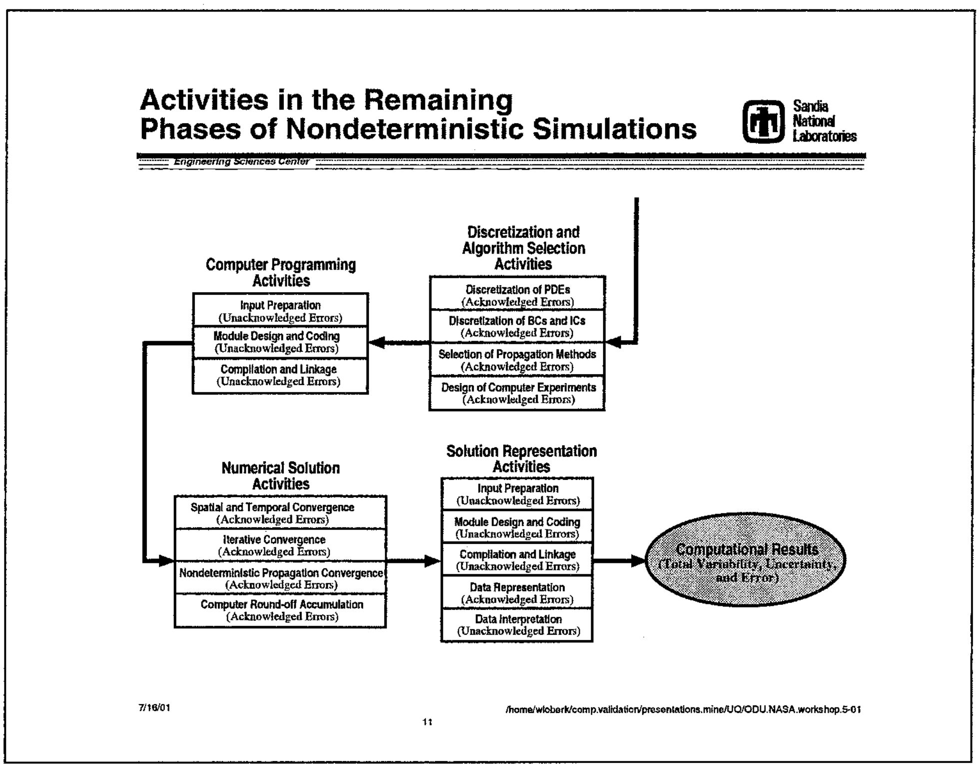

Figure 10

TREE-STRUCTURE FOR MODELS, SOLUTIONS, AND REPRESENTATIONS

The figure illustrates the multiple models, numerical solutions, and solution representations that are addressed in the missile flight example. As shown in the figure, six conceptual models are identified, many more are implied, but for illustration only one is selected for further development and analysis. This single conceptual model spawns two alternative mathematical descriptions, the 3-DOF and 6-DOF models, both of which are carried through the remaining phases of the modeling and simulation process. For simplicity, only one of these mathematical models shows further development, although it is understood that identical development of Mathematical Model 1 is taking place in parallel with Mathematical Model 2. The discretization and programming phases identify alternative model choices that are not considered further in this example. Continuing into the numerical solution phase, nondeterministic effects that were identified in the conceptual model and further defined in the mathematical modeling phase are computed via multiple deterministic numerical solutions. How these solutions were computed was specified in the propagation method identified in the discretization and algorithm selection phase. Finally, in the solution representation phase, the multiple solutions are merged to represent the complete nondeterministic solution.

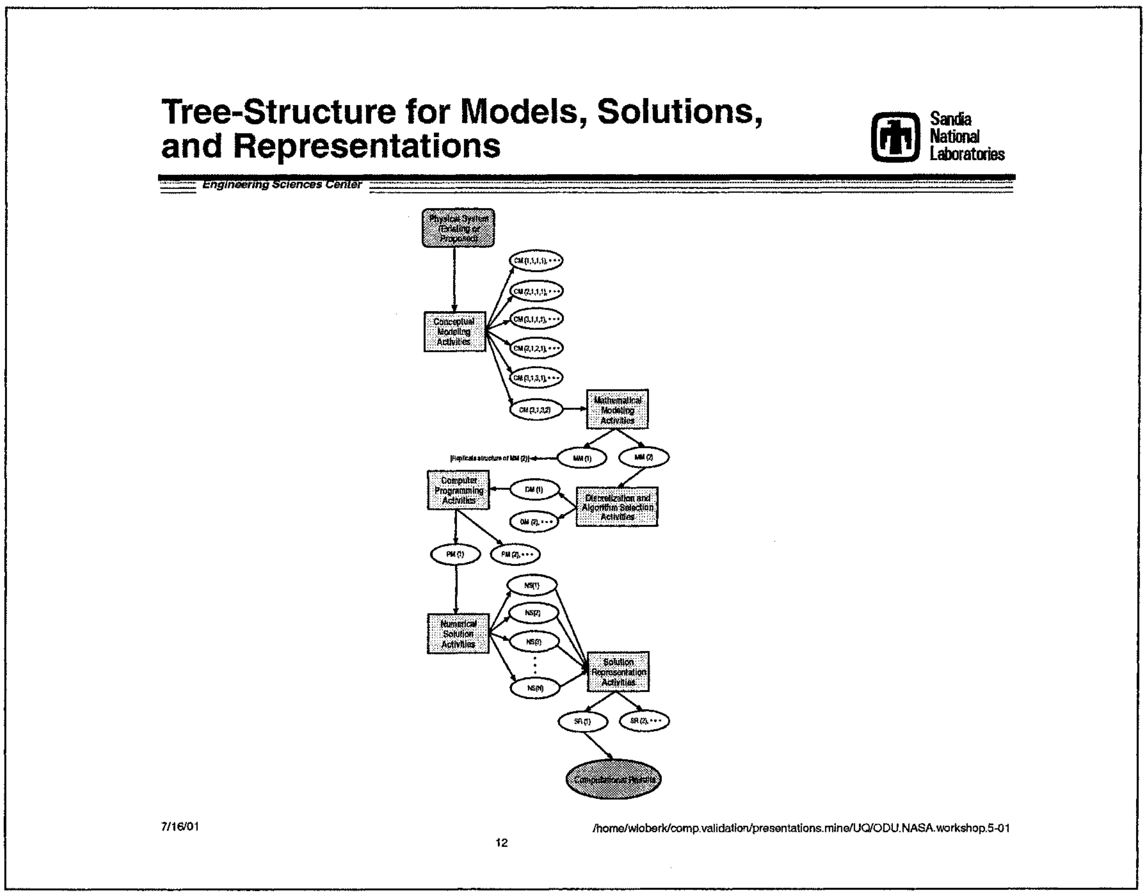

Figure 11

SUMMARY AND CONCLUSIONS

We have presented a comprehensive, new framework for modeling and simulation that blends the perspective of three technical communities: the systems view from the operations research community, propagation of uncertainty from the risk assessment community, and the numerical solution of PDEs from the computational physics community. The activities that are conducted in each of the six phases of modeling and simulation were discussed. We carefully define and distinguish between uncertainty and error. Our framework applies regardless of whether the discretization procedure for solving the PDEs is based on finite elements, finite volumes, or finite differences. The formal distinction between aleatory uncertainty and epistemic uncertainty in this framework drives one toward different mathematical representations for each type of uncertainty. Probabilistic representations are clearly appropriate for aleatory uncertainty, and various other modern information theories are, we believe, more appropriate for epistemic uncertainty. We recommend research into evidence (Dempster/Shafer) theory. This theory, however, is not well developed when compared to traditional probabilistic methods. If one were to take the step and represent aleatory uncertainty probabilistically and epistemic uncertainty with evidence theory, then one must face the question of propagating these components concurrently through the modeling and simulation process. Propagation of Belief and Plausibility measures from evidence theory through complex PDE models is a research topic.

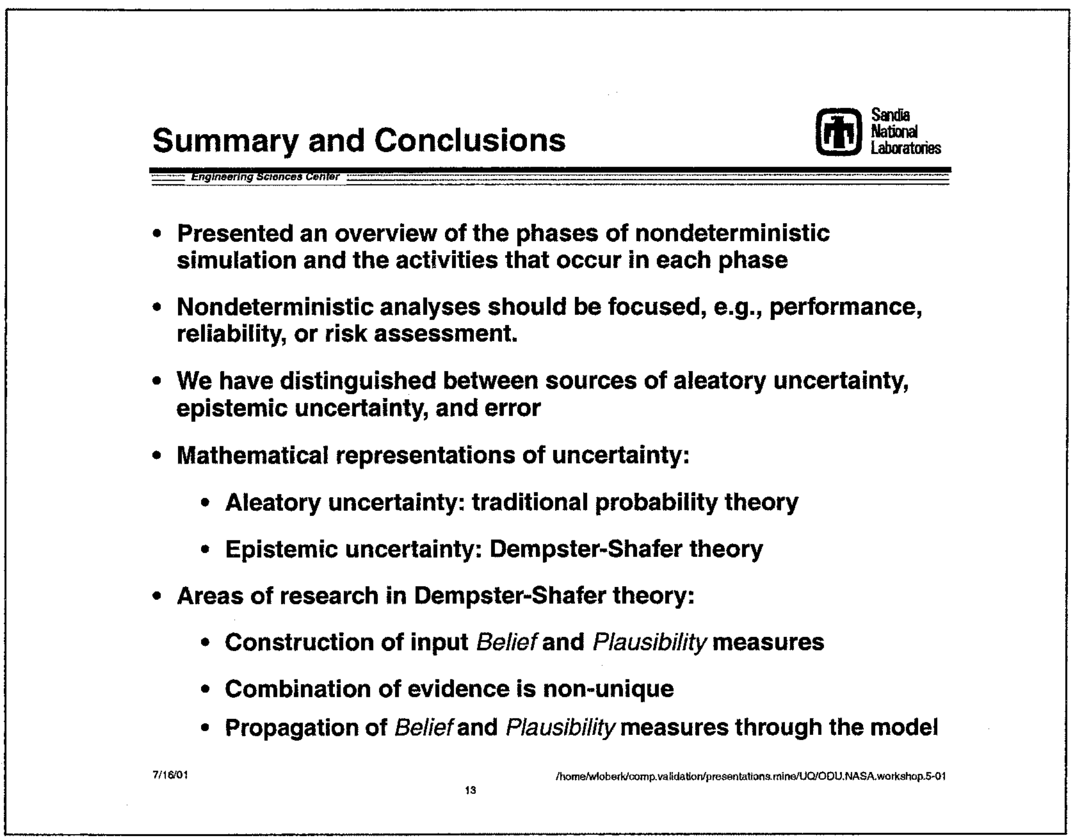

Figure 12

Errors and Uncertainties in Probabilistic Engineering Analysis

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Errors and Uncertainties in Probabilistic Engineering Analysis

Ben H. Thacker, David S. Riha,
Harry R. Millwater and Michael P. Enright
Southwest Research Institute

ODU-NASA Training Workshop on Non-deterministic Approaches and Their Potential for Future Aerospace Systems
Reid Conference Center, NASA/LARC, 30-31 May 2001

42nd AIAA/ASME/ASCE/AHS/ASC SDM Conference and Exhibit
Seattle, Washington, 16-19 April 2001

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Figure 1

Outline

- Introduction
- Motivation
- Sources of Error in Probabilistic Analysis
- Example Problems
- Proposed Strategy
- Summary and Conclusions

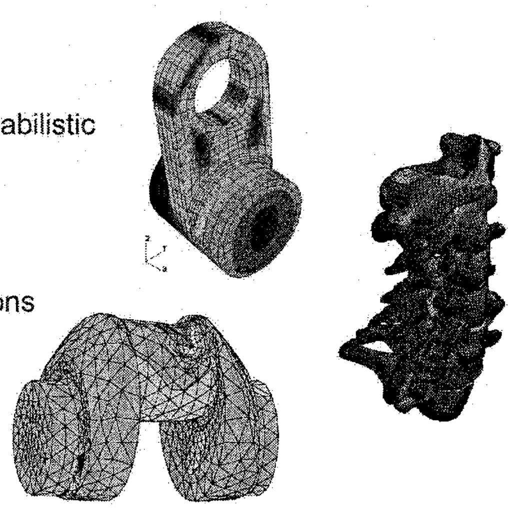

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Figure 2

Motivation

- Confidence in probabilistic assessments is required to support
  - Certification
  - Design analysis
  - Critical decisions
- First step towards verification and validation of probabilistic models
- Understanding where errors originate will suggest more robust computational strategies

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Figure 3

Sources of Error in Probabilistic Analysis

- Model approximation
  - First or second-order approximation
  - Calculation of derivatives
- Uncertainty characterization
  - Insufficient data
  - Selection of incorrect distribution
- Probability integration
  - Insufficient number of samples
  - First or second-order approximation
- Numerical algorithm
  - Transformations to standard normal
  - Convergence error in finding the MPP
  - Algorithm error (wrong or multiple MPP)

- **All forms of error are reducible**
  - **V&V of the probabilistic analysis**
  - **Increased data collection**
  - **Development of more accurate and robust analysis methods**

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Figure 4

Algorithm Error is Most Troublesome

- Source of error is inability of the algorithm to locate the correct MPP
  - local minimum
  - multiple minimums
  - violations of the assumptions of a smooth and continuous response surface.
- For robustness, algorithm must be able to locate all MPP's
- Troublesome aspect is that problem can arise after transformation to standard normal, unbeknownst to the user
- Can occur when mapping from original to standard normal space

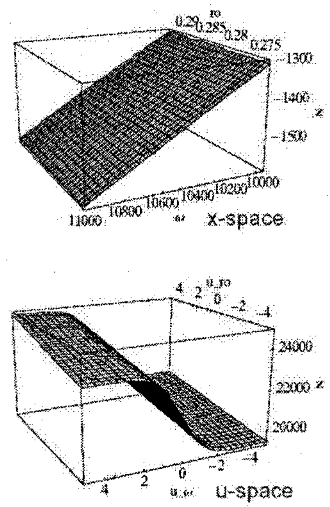

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Figure 5

Probabilistic Analysis Methods

- Fast Probability Integration Methods
  - Advanced mean value
  - First and second-order reliability methods
  - Fast convolution integration using FFT
- Sampling Methods
  - Monte carlo simulation
  - Sphere-based importance sampling
  - Latin hypercube simulation
  - Adaptive importance sampling
- Probabilistic fault-tree
- Response surface method

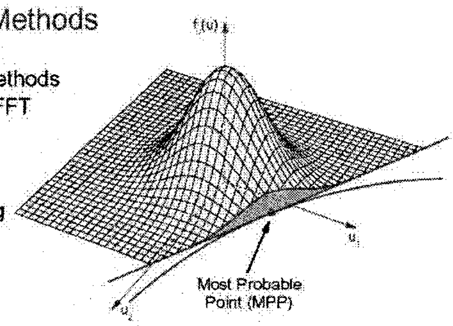

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Figure 6

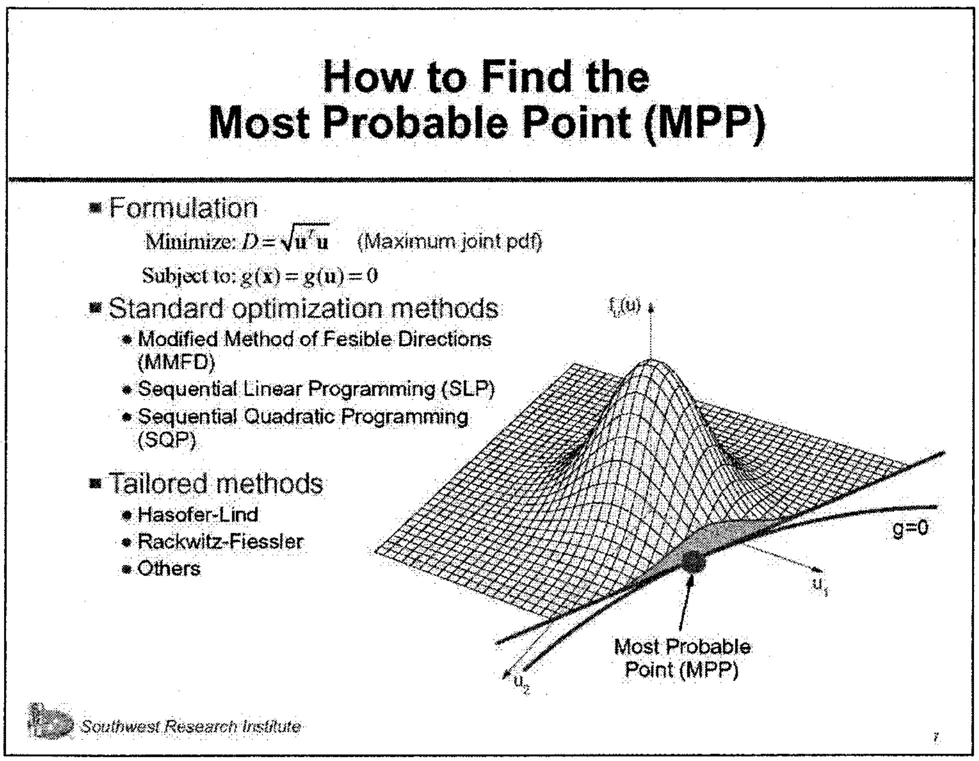

Figure 7

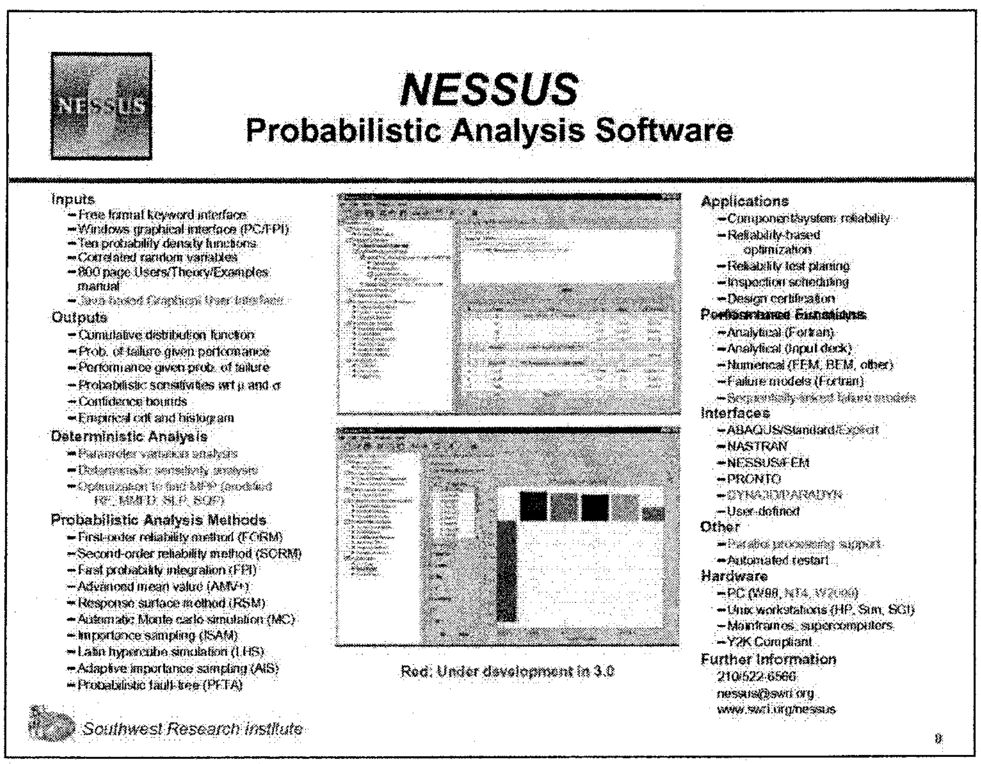

Figure 8

Convergence Criteria
"Modified RF" Optimization

- Checking only β may not be sufficient
  - g_3 has multiple mpp's
  - β may stabilize (converge), but the MPP may not
- Check angle between successive MPP during iteration

$$\theta = \cos^{-1}[\mathbf{u}_1 \mathbf{u}_2]$$

- Also check g=0. Summary:

$$\varepsilon_1 = \left|\beta_{i+1} - \beta_i\right| / \beta_i \le \text{tol1}$$
$$\varepsilon_2 = \left|\theta_{i+1} - \theta_i\right| / \theta_i \le \text{tol2}$$
$$\varepsilon_3 = \left|g(X_i)\right| \le \text{tol3}$$

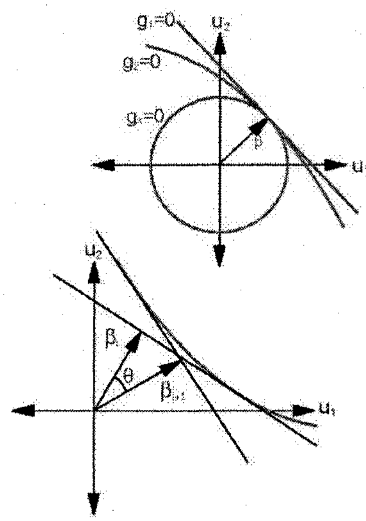

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Figure 9

Example Problems

- Three examples solved
  - From SAE G11 Probabilistic Methods, Numerical Review Subcommittee
- Goal is to investigate accuracy and error (not efficiency)
- Solutions obtained using
  - Monte Carlo (MCS)
  - First-order Reliability Method (FORM)
  - Second-order Reliability Method (SORM)
  - Advanced Mean Value (AMV+)
  - Adaptive Importance Sampling (AIS)
  - Response Surface Method (RSM)
- NESSUS 3.0 software used for all problems
  - Modified Rackwitz-Fiessler (RF) attempted first
  - If problems, switched to sequential quadratic programming (SQP)

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Figure 10

Example Problems - The Details

- Monte Carlo
  - 100M samples
  - 95% confidence bounds
- AMV+
  - 5% iteration tolerance
- AIS
  - Second order (curvature based)
  - 5% error and 95% confidence
- RSM
  - Central Composite (CC) design used
  - 10M samples
  - r^2 reported for each problem
  - 2σ move limits on each random variable

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Figure 11

Example 1 - Gear Contact Stress Model

Response given by

$$Z=\sigma_{g}^{2}\frac{2T_{p}EP_{d}^{3}\sin\phi}{(1-\nu^{2})\pi\lambda N_{1}^{2}\theta_{1}\cos^{2}\phi\left[\sin\phi-\dfrac{\theta_{1}\cos\phi}{(m_{g}+1)}\right]}$$

where

$$\theta_{1}=\text{Rollangle}=\frac{2\left\{\sqrt{\left(\dfrac{N_{1}}{2}\sin\phi\right)^{2}+N_{1}+1}-\pi\cos\phi\right\}}{N_{1}\cos\phi}$$

and

$$\lambda=f\frac{P_{d}}{N_{1}}$$

Var	Name	Mean	SD	Dist
1	Face width (in.)	0.5	0.025	Normal
2	Pressure angle (deg.)	20	1.0	Normal
3	Torque (lb-in)	108	5.4	Normal
4	Modulus of elasticity (ksi)	30000	1500	Normal
5	Diametral pitch (1/in.)	9	0.45	Normal
6	Allowable surface pressure (ksi)	88	4.4	Normal
7	Number of teeth of the pinion	18	0.9	Normal
8	Poisson's ratio	0.25	0.0125	Normal
	Gear ratio	3.78	-	-

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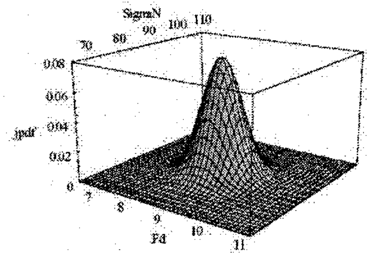
Figure 12

Example 1 - Gear Contact Stress Model

- Linear transformation (normal to standard normal)
- Response surface same in x-space and u-space



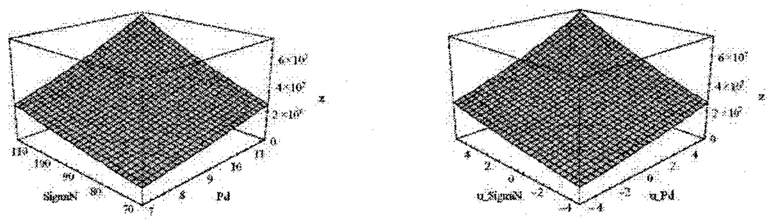


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Figure 13

Example 1 - Gear Contact Stress Model

- All methods compare reasonably well
- RSM in error in left tail
  - Due to fit around central region
- But what is the error?

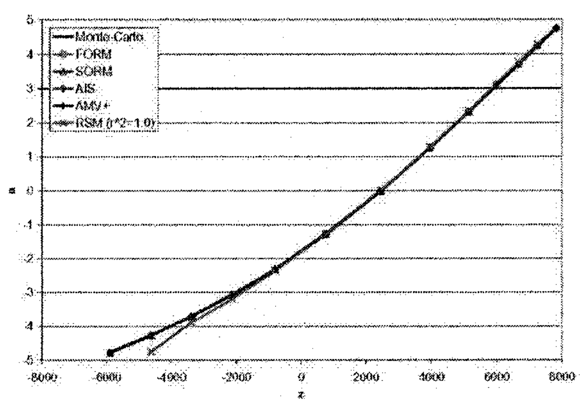

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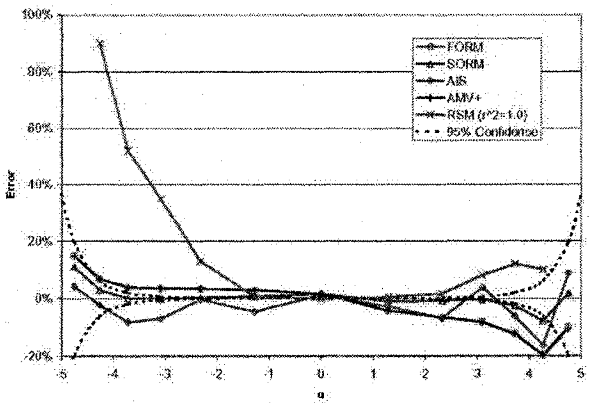
Figure 14

Example 1 - Gear Contact Stress Model

- Percent error from Monte Carlo solution (100M samples)
- 95% confidence bounds
- All methods posses some error
  - x-space and u-space function approximation
  - convergence tolerance



Even for mildly nonlinear problems, accurate function approximations in x and u-space are important

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Figure 15

Example 2 - Maximum Radial Stress of a Rotating Disk

- Response function

$$(\sigma_r)_{max} = \left(\frac{3+\nu}{8}\right)\left(\frac{\rho}{(9.81)(39.37)}\right)\left(\omega\frac{2\pi}{60}\right)^2\left(r_o^2 - r_i^2\right)$$

- Random Variables

Var	Name	Mean	SD	Dist
ν	Poisson's Ratio	0.30	0.005	Normal
ρ	Density (lb/in3)	0.284	0.002	Normal
ω	Rotor Speed (rpm)	10500	288.7	Uniform (10000,11000)
ro	Outer Radius (in)	8	0.02	Normal
ri	Inner Radius (in)	2	0.01	Normal

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Figure 16

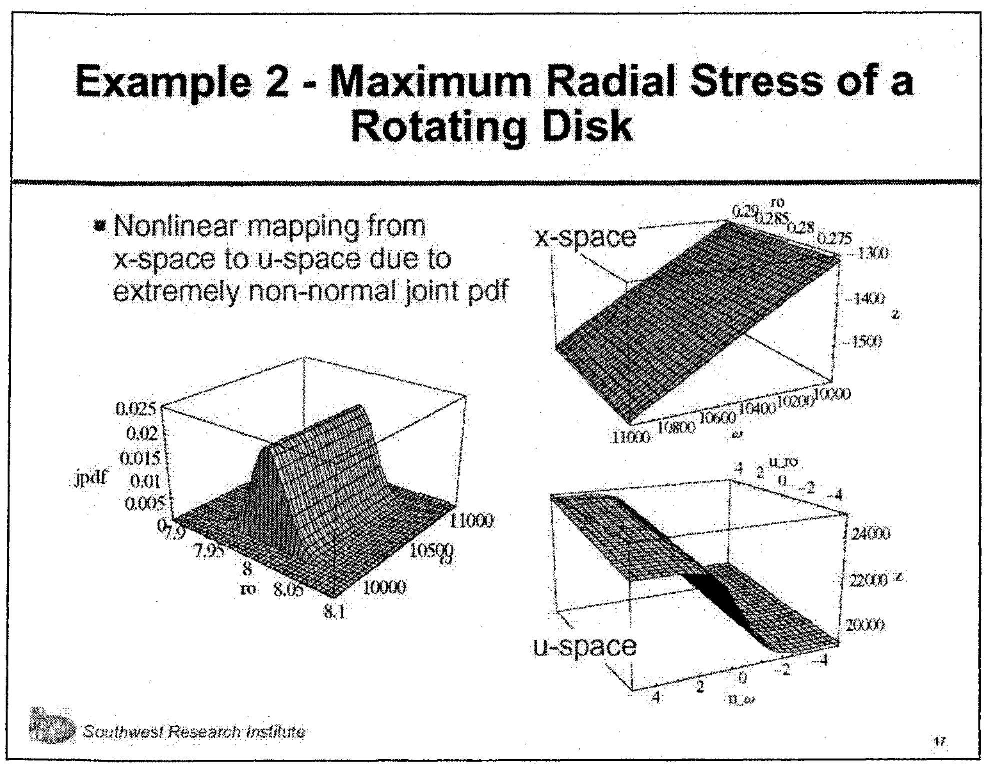

Figure 17

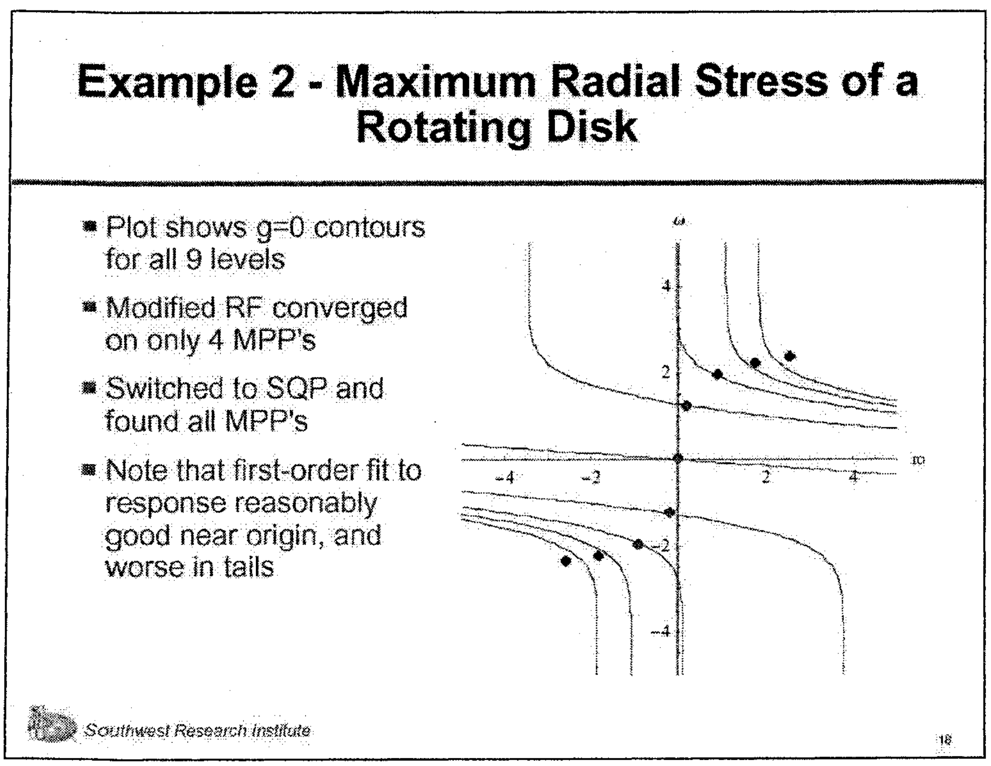

Figure 18

Example 2 - Maximum Radial Stress of a Rotating Disk

- At this scale, all methods appear to have done well
- Some error in tail regions

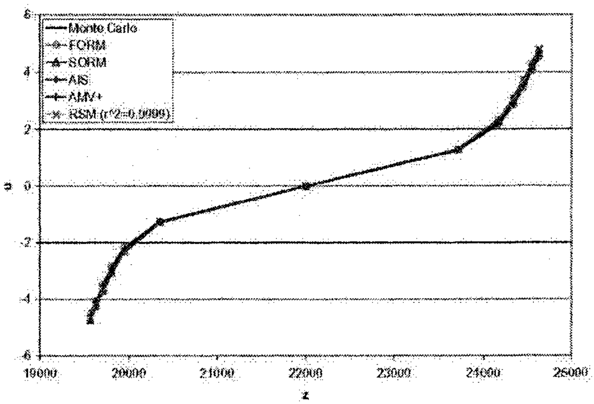

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Figure 19

Example 2 - Maximum Radial Stress of a Rotating Disk

- Right tail shown
- Good solutions from SORM, AIS, and RSM
- Systematic error in FORM and AMV+ solutions

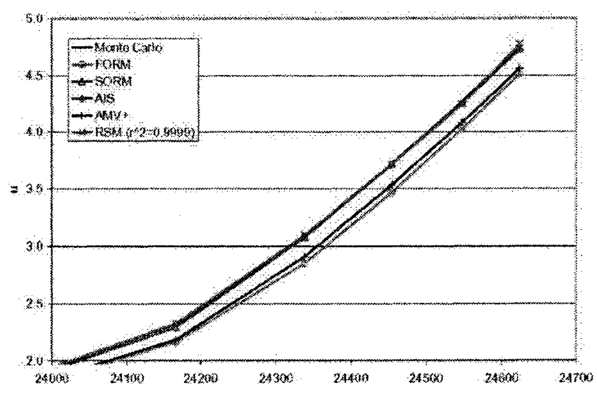

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Figure 20

Example 2 - Maximum Radial Stress of a Rotating Disk

- Plot shows magnitude of error can be quite large even for converged solutions
  - FORM & AMV+
- SORM and AIS perform very well, even though u-space is highly nonlinear
- RSM performs well because fit in x-space is good.
  - Large left tail error in RSM is sampling error

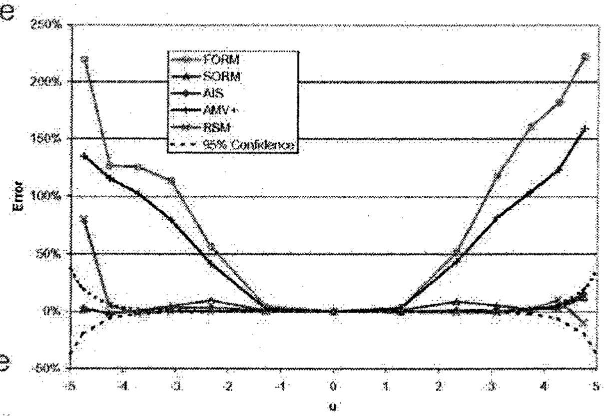

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Figure 21

Example 2 - Maximum Radial Stress of a Rotating Disk
Lessons Learned

- First-order approximation in u-space may not be accurate for highly nonlinear function
  - Nonlinear in x-space
  - Nonnormal transformation
- AMV+ converges on location of MPP. Computed probability then depends on what order of approximation is used.
- AMV+ used here is based on first-order. Second order available, but not used very often.
- Recommendation is to use AMV+ to locate MPP. Then use AIS to compute probability.

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Figure 22

Example 3 - Multiple MPP Problem

- Response function

$$Z = 3 + 2X_1^4 - X_1^2 - X_2$$

- X_1~N[0,1]
- X_2~N[0,1]
- Response surface same in u-space and x-space
- Slight nonlinearity in X_2

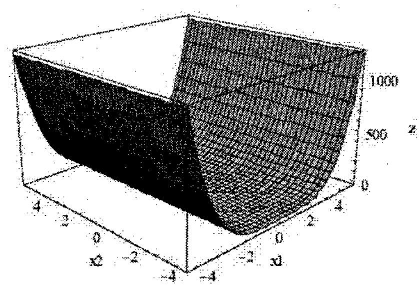

Figure 23

Example 3 - Multiple MPP Problem

- g=0 levels numbered in contour plot
- Again, the modified RF algorithm reported convergence errors.
- Switched to SQP and found one MPP per limit state
- Function is symmetric about X2 - therefore, two MPP's exist.
- Solutions reported on following charts are based on one (shown) MPP

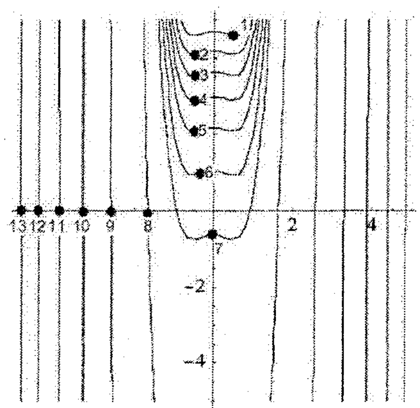

Figure 24

Example 3 - Multiple MPP Problem

- Very steep cdf in left tail
- Unable to discern difference in solutions
- Systematic error in right tail observed
- RSM obviously bad
  - Full quadratic is poor approximation to original function
  - Using wider move limits improved tail, but at expense of central region

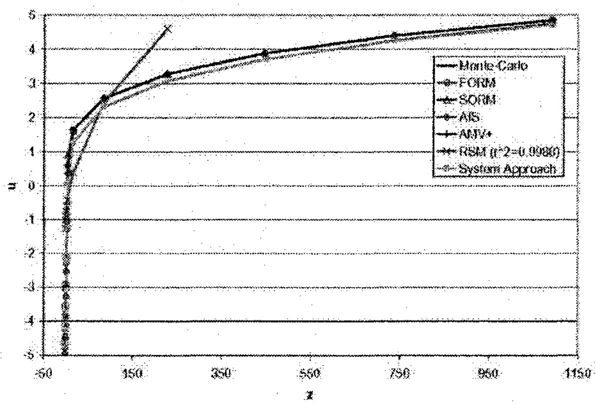

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Figure 25

Example 3 - Multiple MPP Problem

- Left tail response shown
- Error observed at levels 1-6 by all methods
- Error due to use of only one MPP
- RSM error due to poor function approximation

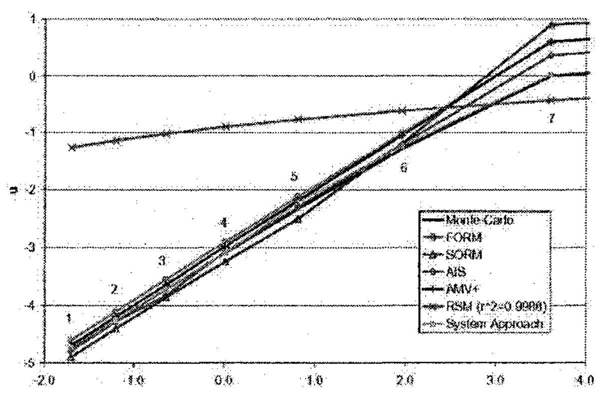

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Figure 26

Example 3 - Multiple MPP Problem

- Percent error plot
- All methods have significant error
- Need a more general approach that can automatically
  - switch optimizers if trouble encountered
  - identify multiple MPP's
  - solve multiple MPP problem

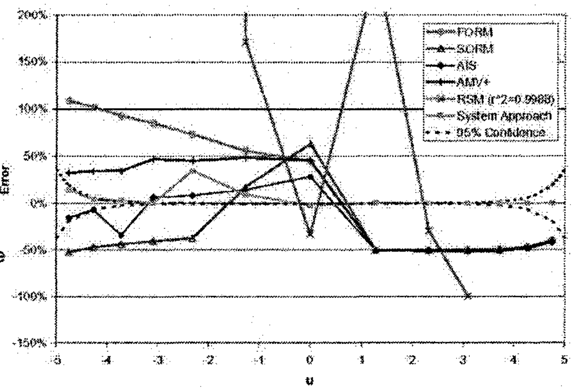

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Figure 27

Proposed Strategy: System Approach

- Case 5, Level 4 studied in more detail
- Monte Carlo sampling on transformed response function (u-space)
- 2M samples used, but still fast
- 10 minimum β points

Sample No.	Angle (degrees)	Beta
1	0.00	2.915
2	18.50	2.918
3	17.00	2.918
4	17.80	2.920
5	19.10	2.921
6	17.90	2.921
7	17.50	2.921
8	0.80	2.923
9	0.70	2.926
10	1.50	2.925

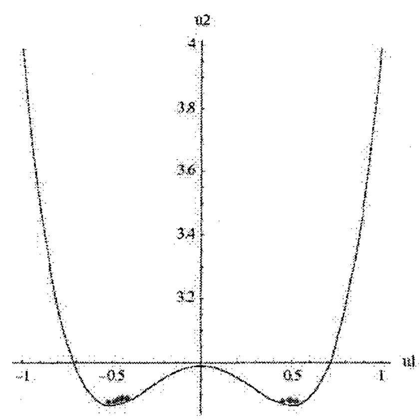

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Figure 28

Proposed Strategy: System Approach

- Use NESSUS probabilistic fault tree to solve multiple MPP problem
- Adaptive Importance Sampling used to compute union of two limit states
- Sampling based MPP search and system probability calculation applied to each level
- Excellent results obtained

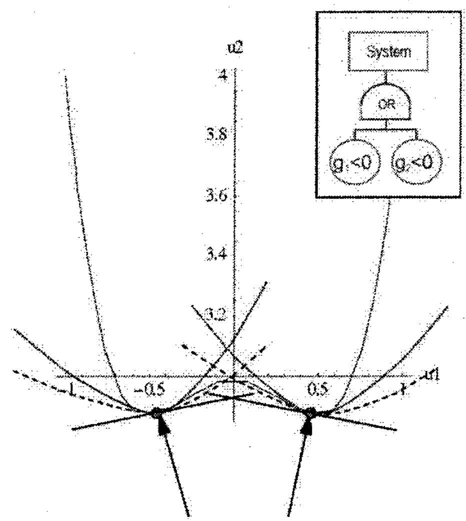

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Figure 29

Summary

- All forms of error are reducible
  - V&V of the probabilistic analysis
  - Increased data collection
  - Development of more accurate and robust analysis methods
  - Assessed via deterministic or probabilistic analysis
- Types of errors in probabilistic analysis
  - Model approximation
  - Uncertainty characterization
  - Probability integration
  - Numerical algorithm
- Various errors quantified in paper using simple analytical models
- Simple but effective strategy used to solve multiple MPP problem

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Figure 30

Conclusions

- For challenging problems, trained analysts are required to compute accurate solutions
- Advanced mean value (AMV+) method and the modified RF optimizer were the only methods that identified when problems were occurring
- Solutions to difficult problems (multiple MPP) can be solved using existing methods, but detailed knowledge of the problem is required
- Robustness of computer code not only measured by its ability to ***get a*** solution, but to ***get the right*** solution
  - Solution error must be quantified before confidence is gained
  - Methods must warn when problems are suspected
  - Adaptive/intelligent methods can produce accurate solutions

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Figure 31

Acknowledgments

- Southwest Research Institute Advisory Committee for Research
- Los Alamos National Laboratory

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Figure 32

Practical Implementation of Probabilistic Technology

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OUTLINE

Existing predictive technologies
Probabilistic technology
Practical software architecture
Typical Inputs
Typical outputs
Examples
Latest development in probabilistic software tools

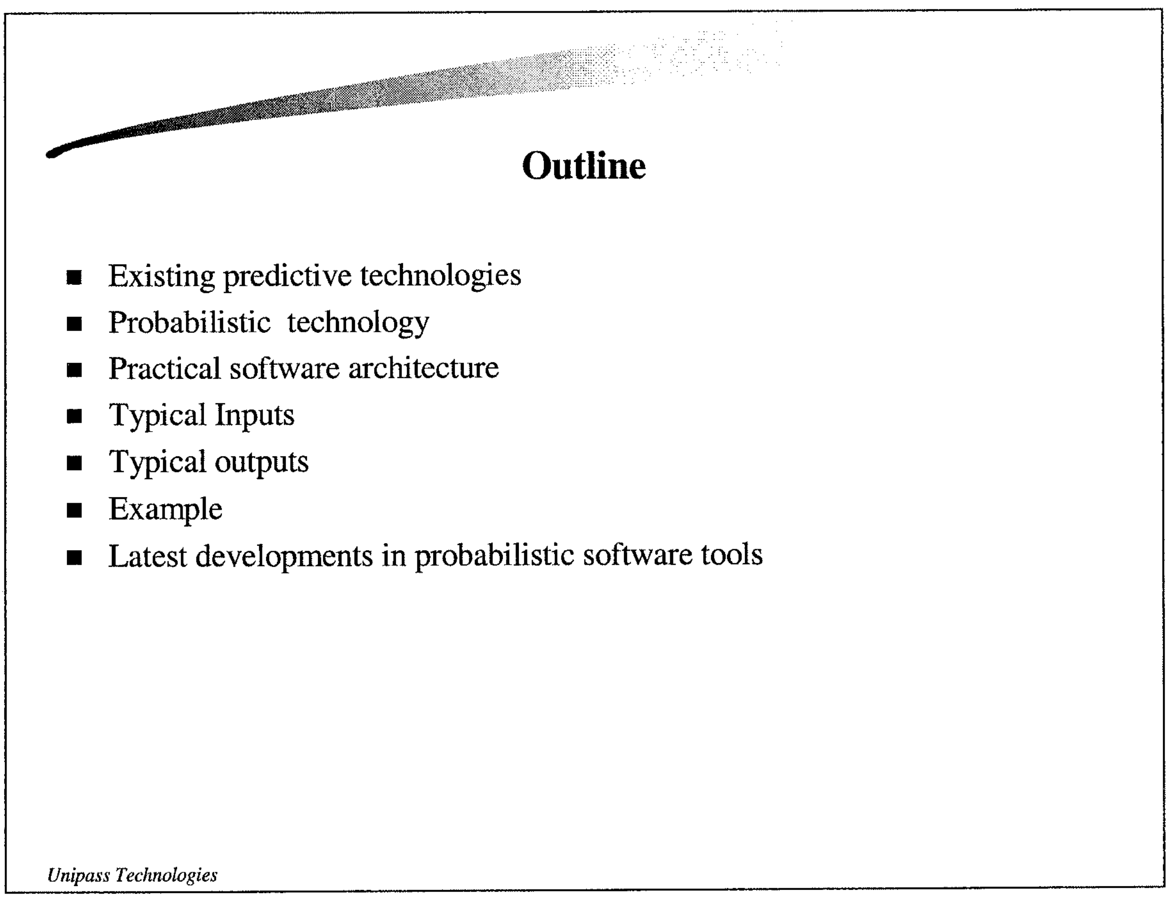

Figure 1

EXISTING PREDICTIVE TECHNOLOGIES

Traditionally, predictive analyses have used either a *deterministic* or a *statistical* approach. The deterministic approach attempts to predict the outcome of a process or event using physics-based mathematical models of the event by assigning single values to the variables that enter these models and affect the outcome. Furthermore, the deterministic approach also assign a safety factor to the outcome in order to account for the overlooked variability and uncertainties.

In contrast, the statistical approach relies on pure statistical data of process or event out come that can often be flawed or difficult to obtain. Both of these approaches work in isolation, failing to consider any other factors that may significantly affect the result.

Existing Predictive Technologies Have Many Shortcomings

- Deterministic approaches
  - Develop a deterministic event model using physics, process, rules, etc
  - Assign a *single value* to each deterministic event model variable and calculate a *single value* for the outcome
  - Calculate a *single adjusted value* of the outcome by applying a safety factor to the calculated outcome to compensate for uncertainties
  - Predict future of the event using the *single adjusted value* of the outcome
  - Confirm and/or calibrate the *single adjusted value* by tests and/or field data
- Statistical approaches
  - Collect *sufficient* statistical data for the *similar event outcome*
  - Calculate mean, variance, and distribution of the the event outcome using collected data
  - Predict future of the event using the mean, variance, and distribution of the the event outcome

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Figure 2

PROBABILISTIC TECHNOLOGY

The probabilistic analysis begins by developing the deterministic models of the process and identifying the uncertainties associated with such process. There are two type of uncertainties that should be identified, namely, Type I Uncertainties and Type II Uncertainties. The Type I Uncertainty representing the inherent uncertainties associated with the deterministic model variables (e.g., variability of the load in a stress model that calculates the stress under the effect of such load) while the Type II Uncertainties are the uncertainties that are not covered under the Type I Uncertainties (e.g., uncertainties associated with lack of statistical data, model imperfection, human error, measurement error, etc.). If necessary, new variables should be defined to represent Type I and II Uncertainties. Upon completion of the deterministic models and identification of the uncertainties, the Probabilistic Process Models (PPM) should be built. These models describe the outcome of an event using the deterministic models and the Uncertainty Type I and II variables. The Variable Probability Distribution Models (VPDM) is built using the available test/field data and/or the analyst judgment. The PPM and VPDM are then used to perform probabilistic analysis utilizing a probabilistic software engine (e.g., *UNIPASS*™).

Probabilistic Technology Eliminates
The Shortcomings of The Existing Technologies

- Probabilistic approaches
  - Develop a deterministic process models using physics, process, rules, etc
  - Identify uncertainties associated with the deterministic-process-models variables (Type I Uncertainties)
  - Identify uncertainties that are *not* associated with the deterministic- model variables (Type II Uncertainties)
  - Define new variables representing Type I Uncertainties if necessary (Type I Uncertainty Variables)
  - Define additional variables representing Type II uncertainties (Type II Uncertainty Variables)
  - Develop a probabilistic-process-model by incorporating all Type I and II Uncertainty Variables into deterministic event model
  - Develop variable statistical models for all variables including deterministic model variables, Type I Uncertainty Variables, and Type II uncertainty Variables using test/field data and/or analyst judgment
  - Perform probabilistic analysis using probabilistic event model and statistical variable models
  - Predict future of the event using the obtained results
  - Calibrate/update models using tests and/or field data

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Figure 3

PROBABILISTIC TECHNOLOGY

The probabilistic approach incorporates the best of deterministic and statistical methods. This is achieved by using the deterministic process models and enhancing them by taking into account the uncertainties associated with the process and variables (e.g., inherent uncertainties, modeling and measurement errors, lack of data, etc.) and identifying the individual factors that are key to predicting a likely outcome. This approach optimizes the analysis, zeroing in on the factors that actually drive the process.

As oppose to statistical approach the probabilistic technology utilizes the information regarding the variables that enter the process models and affect the outcome and does not require process statistical data for the analysis, however, such data may be used to fine tone the predictive models. Furthermore, the technology quantifies the safety measures and prediction accuracy by providing probabilities associated with the process outcomes.

Probabilistic Technology
Is Superior to The Existing Predictive Technologies

Predictive Technology Comparison Chart

METHODOLOGY APPROACH	DETERMINISTIC	STATISTICAL	PROBABILISTIC
Utilizes physics/behavioral/rule/process based predictive model	✓	X	✓
Considers inherent uncertainties, modeling uncertainties, lack of data, human error, measurement error	X	X	✓
Compensates for unknowns using:	SF	SM	SM
Utilizes past performance data to improve accuracy	✓	✓	✓
Does not require event's past performance data to develop predictive model	✓	X	✓
Quantifies safety measures	U	U	✓
Quantifies prediction accuracy	U	U	✓

✓ TRUE X FALSE U UNKNOWN SF SAFETY FACTORS SM STATISTICAL METHODS

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Figure 4

PRACTICAL SOFTWARE ARCHITECTURE

A practical software architect works through the combination of one or more databases containing the information about the process variables and/or outcome; a *Filter* software that cleans up the databases using a series of rules identified by the analyst; a software engine that reads the data from the databases and identifies the best Variable Probability Distribution Models (VPDM) for the process variables (e.g., our *ProFit*™ software); a software engine that can create the Probabilistic Process Model (PPM) using the deterministic models, from the deterministic software systems, and the information residing in the databases (e.g., our *ProModeler*™ software); and probabilistic engine (e.g., our *UNIPASS*™ software engine) that perform the probabilistic analysis. The PPM is a mathematical representation of how an event works which may be behavior, process, physics and/or rule based. The VPDM is the probability distribution of the PPM's variables.

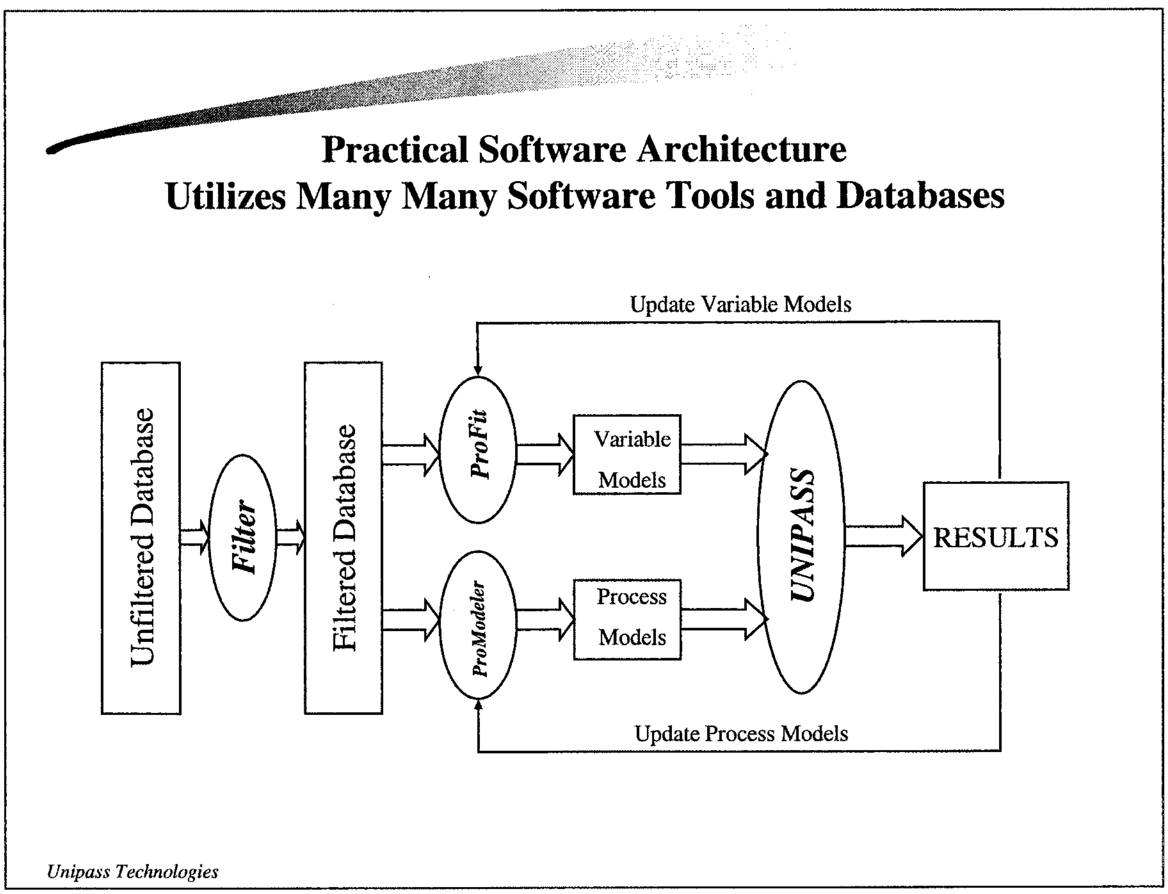

Figure 5

TYPICAL INPUTS

The probabilistic analysis requires four essential items including (a) the Probabilistic Process Models (PPM) that describe the outcome of an event and are constructed using the deterministic models (e.g., a finite element model or a crack growth model) and the mathematical models that describe the uncertainties and are not considered in the deterministic models (e.g., lack of statistical data, modeling error, human error, measurement error, etc.); (b) the PPM's Deterministic Variables; (c) the probability distribution models that describe the randomness of the Uncertainty Type I Variables (e.g., Type I Uncertainties); and (d) the probability distribution models that represent the randomness of the Uncertainty Type II Variables (e.g., Type II Uncertainties).

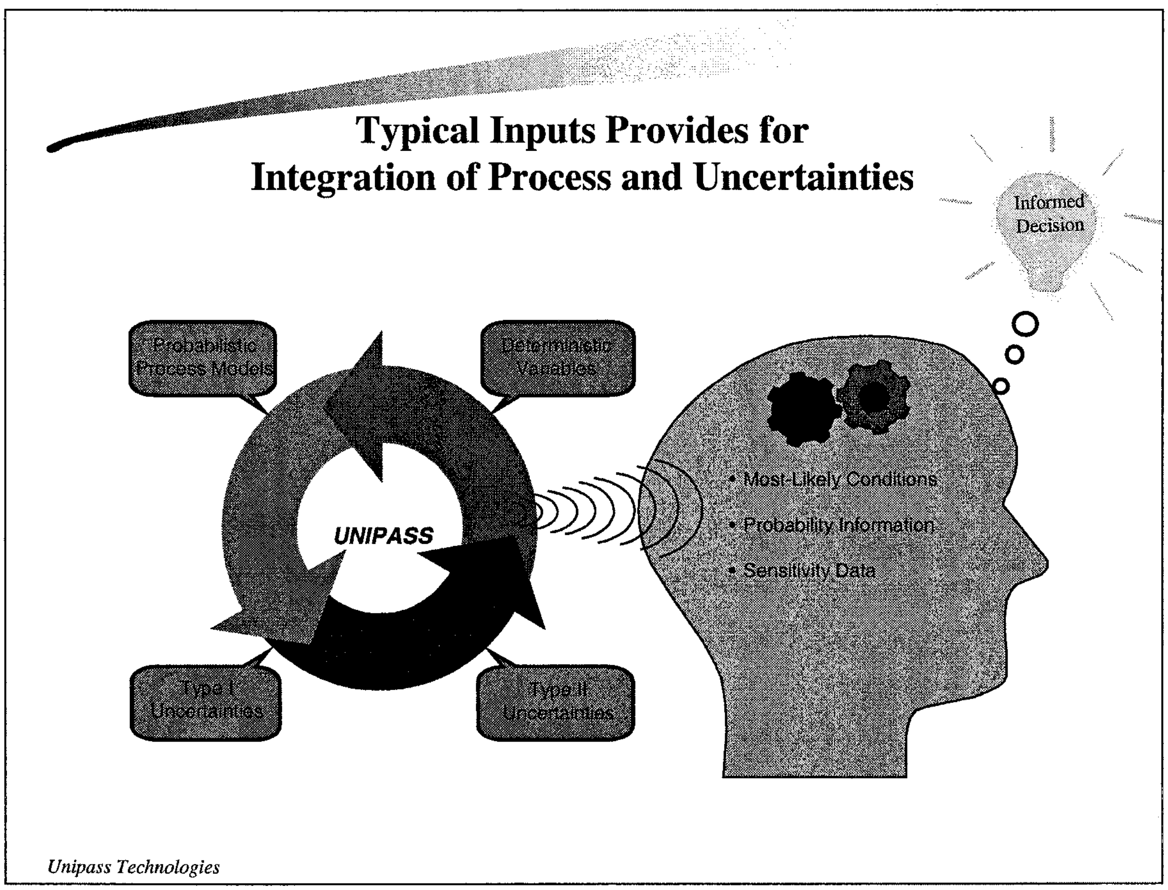

Figure 6

TYPICAL INPUTS - DEFINING VARIABLE PROBABILITY DISTRIBUTION MODELS

Large Amount of Data Available: One of the following techniques may be use to construct the Variable Probability Distribution Models (VPDM) when large amount of data is available (more than 50 data point).

Approach 1: Assume a distribution type and calculate the distribution parameters using the method of moments. Perform the goodness-of-fit tests to eliminate the unacceptable distributions. Use probability paper approach to select the best distribution in the desired range.

Approach 1: Assume a distribution type and calculate the distribution parameters using the maximum likelihood method. Perform the goodness-of-fit tests to eliminate the unacceptable distributions. Use probability paper approach to select the best distribution in the desired range.

Typical Inputs Include Variable Models

- Large amount of data available
  - Distribution type: identify distribution type using probability paper and/or goodness-of-fit-tests. Must have large amount of data (usually 50-100 points) to discriminate between distribution types. Common tests are K-S test and anderson-darling test (preferred). Identify distribution type using probability paper and/or goodness-of-fit-tests
  - Distribution's parameters: calculate distribution's parameters using method of moments or maximum likelihood estimator for the selected distribution type

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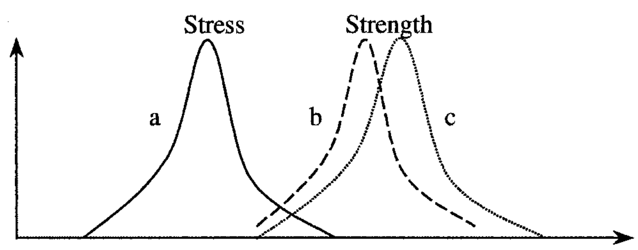
Figure 7

TYPICAL INPUTS – DEFINING VARIABLE PROBABILITY DISTRIBUTION MODELS

Small Amount of Data Available: Assume a distribution type and calculate the distribution parameters using the maximum likelihood method. Utilize hyperparameterization (assume parameters of the random variables to be random variable themselves) to account for lack of sufficient data. Use probability paper and/or the goodness-of-fit test approach to identify all acceptable distribution types within the desired range. Select the distribution that provides for the most conservatism.

Typical Inputs Include Variable Models

- Small amount of data available
  - Distribution's parameters: Calculate distribution's parameters using maximum likelihood estimator for the selected distribution type and use hyperparameterization to consider uncertainty due to lack of statistical data
  - Distribution Type: Select a distribution that is conservatively consistent with the available data



"a" and "b" are more conservative than "a" and "c"

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Figure 8

TYPICAL INPUTS – DEFINING VARIABLE PROBABILITY DISTRIBUTION MODELS

Very Limited Amount of Data Available: Assume Beta or Uniform distribution type. Use hyperparameterization for poorly quantified physical bounds.

No Data Available But Engineering Analysis Exists: Construct a user-defined distribution as shown in the example below.

Typical Inputs Include Variable Models

- Very limited amount of data available
  - Use Uniform or Beta (good quantification of physical bound)
  - Use Uniform or Beta with Hyperparameterization (poor quantification of physical bound)
- No data available but engineering analysis exists
  - User defined distribution
  - Example
    - ➢ Worst stress value from FE analysis 120 ksi
    - ➢ Maximum spread between best and worst condition is 20 ksi
    - ➢ Actual stress could be off by 10%
    - ➢ Stress = C (120-S)

      Where C is uniform between 0.9 and 1.1 and S is uniform between 0 and 20

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Figure 9

TYPICAL INPUTS – DEFINING VARIABLE PROBABILITY DISTRIBUTION MODELS

No Data or Engineering Analysis Exists: Construct a user-defined distribution as shown in the example below.

Typical Inputs Include Variable Models

- No data or engineering analysis available only engineering judgment can be made
  - User defied distribution
  - Example: consider a turbine blade thickness
    - ➢ Nominal value=0.058
    - ➢ Allowable tolerance = ±0.005 which occurs 90% of the time
    - ➢ Maximum deviation outside acceptable tolerance= ±0.002 (10% of the time)

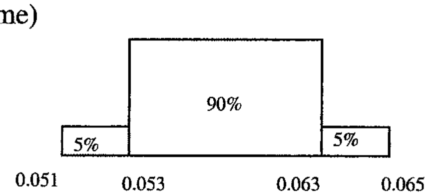

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Figure 10

TYPICAL INPUTS – DEFINING PROBABILISTIC PROCESS MODELS

In general, an event model is a mathematical expression relating a dependent variable y, to a set of observable variables $\underline{x}$, and a set of unobservable model parameters $\underline{z}$. The model is usually constructed on the basis of simplifying principals, and sometimes on purely heuristic basis when underlying phenomenon is not well understood. In addition to *inherent uncertainties,* there are at least three major phenomena that give rise to uncertainty in an event model. These include *model imperfection, measurement error, and statistical uncertainty*. The process of model construction mounts to estimating the unobservable model parameters $\underline{z}$ based on a set of measurements $\underline{x}_i$, and y_i, i=1,.....m of the observable model variables. Following the Bayesian paradigm, we express our lack of precise knowledge about $\underline{z}$ by assigning a probability distribution to it. The Bayesian Updating Rule allows us to combine previous information about $\underline{z}$ with information obtained from observed data to arrive at a distribution.

Typical Inputs Include Process Models

- Known relationship (explicit or implicit)
  - In many instances, the exact theoretical relationship for the predictive model will be well known from a theoretical relationship such as from an engineering handbook or a deterministic code
- Know data to estimate predictive model
  - In some instances, it may be possible to construct an approximation to the predictive model by using regression models of empirical data or similar statistical methods

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Figure 11

TYPICAL OUTPUTS

In general, probabilistic analysis produces three categories of information that would help achieving an informed decision. This includes probability information, most likely conditions, and sensitivity data. These categories are briefly descried in the following charts.

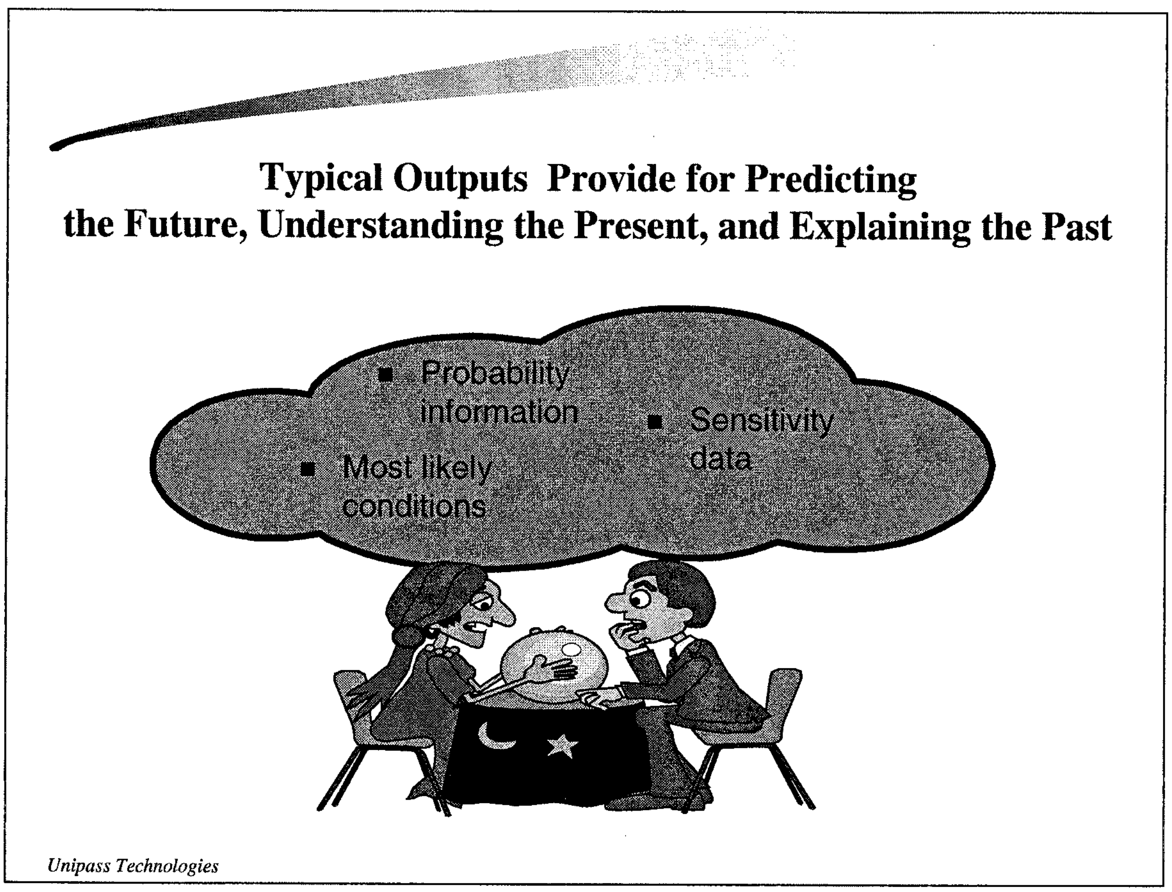

Figure 12

TYPICAL OUTPUTS

Probability Information: The probability information includes reliably, failure probability, cumulative distribution function (CDF),and probability density function (PDF). The probability information may be used to identify the most critical failure mode; estimate the reliability, potential risk, and liability. It may also be used to determine the acceptable response range or calibrate the safety factors.

Most Likely Conditions: The most likely conditions is identified by the most-probable-point (MPP). In general, the MPP represents the most likely values of the random variables at which the critical or significant condition of the user-defined event will occur. In engineering, a critical condition may be an undesirable event such as component failure or instability, or a desirable event such as extended component life or mission success.

Typical Outputs Includes Probability Information, Most Likely Conditions, and Sensitivity Data

- Probability information (e.g., failure probability, reliability, probability values, CDF, or PDF) can be used to:
  - Estimate reliability, failure probability, risk, and liability
  - Calibrate safety factor and identify critical failure mode
  - Minimize number of tests, inspection costs
  - Estimate response range
  - Etc
- Most-likely conditions (e.g., most-probable-point) can be used to :
  - Identify most-likely combination of predictive model variables in the field
  - Certification process tests, reliability demonstration tests, most likely test setups, safety control systems
  - Etc

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Figure 13

TYPICAL OUTPUTS

In performing probabilistic analysis, it is often of interest to determine the sensitivity of event outcome or its calculated probabilities with respect to model variables and their parameters appearing in the event model. These measures are useful for many purposes including but not limited to identification of key event drivers, important sources of uncertainty, optimal condition, resource allocation, and analysis of model uncertainties. Often, these measures also provide insight into the physics of the event.

Typical Outputs Includes Probability Information, Most Likely Conditions, and Sensitivity Data

- Sensitivity information includes physical and probability sensitivities and can be used to:
  - Identify key variables
  - Identify worst load combination
  - Automate processes
  - Minimize number of tests
  - Minimize weight
  - Minimize response variation
  - Minimize number of tight tolerances
  - Minimizes costs (e.G., Development, manufacturing, inspection, maintenance, and/or warranty costs)
  - Etc

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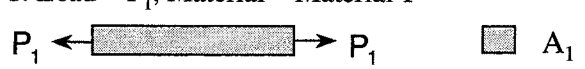
Figure 14

EXAMPLE

The reliability of the Design 2 should be equal or higher than the reliability of Design 1. Investigate the possibility of using the less expensive material (Material 2) using deterministic approach. Check the accuracy of the results using probabilistic analysis.

Example

- Select a material for design 2 that ensures equal or higher reliability than design 1 under the new loading condition
  - Design 1: Load = P_1, Material = Material 1



  - Design 2: Loads = $P_1 - P_2$, Material = ?

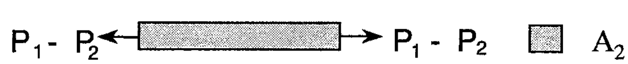


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Figure 15

EXAMPLE

Assuming a safety factor of 1.4 the deterministic analysis predicts a Safety Margin of 0.0 for Design 1 and a Safety Margin of 0.131 for Design 2 using the Material 2.

Analysis Results: Material 2 can be used for Design 2.

Example

- Deterministic analysis strategy
  - Assume a safety factor of 1.4 for both designs
  - Identify the margin of safety for both designs
  - Identify the safer design
- Deterministic analysis results
  - Design 1: margin of safety = 140/(1.4*100) - 1 = 0
  - Design 2: margin of safety = 95/(60*1.4) - 1 = 0.131
  - **Safer design: design 2 (0.131 > 0)**
  - Sensitivity analysis results not available

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Figure 16

EXAMPLE

Assuming Material 2 for Design 2, probabilistic analysis predicts much higher failure probability for design 2 compared with Design 1. This violates the design requirement.

Analysis Results: Material 2 *cannot* be used for Design 2.

Example

- Probabilistic analysis strategy
  - Consider the variation of design parameters (P_1 and P_2)
  - Defines limit-state function, $g = f_{ty\,(min)}$ - calculated stress (P, A), i.E., Failure occurs when calculated stress > $f_{ty\,(min)}$
- Probabilistic analysis results:
  - Design 1: reliability = R_1 = 0.99997
  - Design 2: reliability = R_2 = 0.99942
  - **Safer design: design 1 ($R_1 > R_2$)**
  - Sensitivity analysis results available

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Figure 17

EXAMPLE

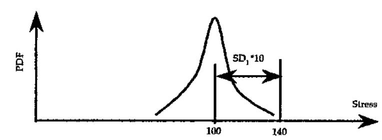
Design 2 is subjected to two random loads with 10% coefficient of variation. This will result in a standard deviation of 10.77 kips for the resultant load spectrum of Design 2. To ensure the same level of reliability for both designs, the number of standard deviation away from mean of the applied load must be identical for both designs. This assumption will result in a safety factor of 1.718 for Design 2. Using the new safety factor, the deterministic approach will also achieve the same results obtained by the probabilistic method.

Example

- Calculate number of standard deviations away from mean (SD_1) for design 1 based on assumed safety factor ($SF_1 = 1.4$)

  $SD_1 = (SF_1*100-100)/10$

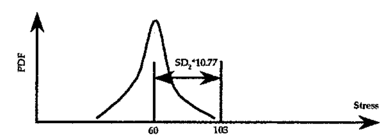
  $= (1.4*100-100)/10 = 4$



- Use the same number of standard deviations ($SD_2 = SD_1$), calibrate safety factor for design 2 (SF_2)

  $SF_2 = (60+ SD_1*10.77)/60$

  $= (60+4*10.77)/60 = 1.718$



- Calculate the required strength for design 2 based on the updated safety factor, SF_2 (original required strength = 60*1.4 = 84 ksi)

  Required Strength = 84 * 1.718/1.4 = 103.08 (> 95, not acceptable)

Same Safety Factors May Not Be Appropriate for All Designs

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Figure 18

EXAMPLE

Assuming the same level of reliability, safety factor is a highly nonlinear function of load and strength uncertainties. This means that the safety factors must be calibrated for structures that are subjected to multiple loads to ensure adequate reliability level.

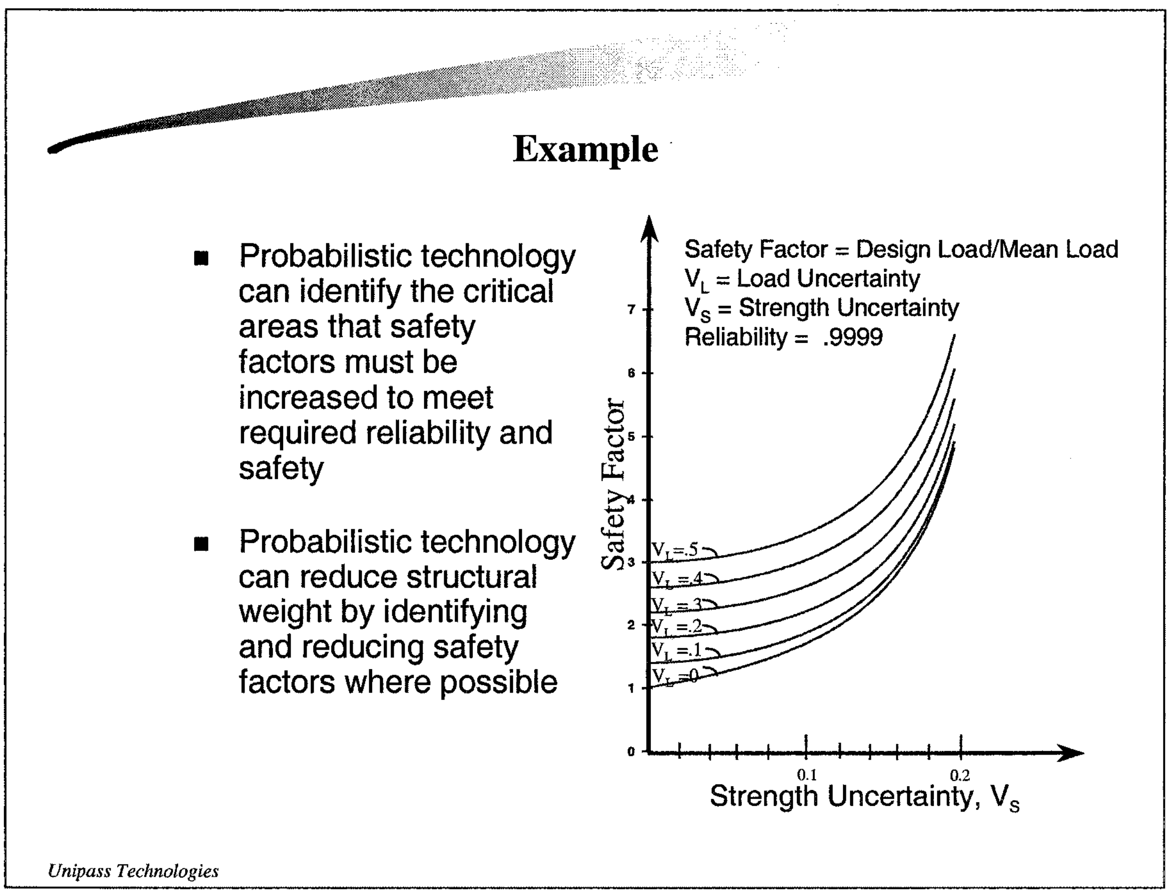

Figure 19

LATEST DEVELOPMENT IN PROBABILISTIC SOFTWARE TOOLS

The following list includes the most recent available probabilistic software tools

UNIPASS, ProFit, and ProModeler by Unipass Technologies
NESSUS by NASA Glenn and SwRI
ProFEA by ARA
ANSYS PSD by ANSYS
PROBAN by Veritas
FEBREL by Boeing

Latest Development in Probabilistic Software Tools Will Allow Companies To Maximize Their Business Success

- ***UNIPASS, ProFit, and ProModeler*** by Unipass Technologies
- NESSUS by NASA Glenn and SwRI
- ProFEA by ARA
- ANSYS PSD by ANSYS
- PROBAN by Veritas
- FEBREL by Boeing
- Etc

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Figure 20

LATEST DEVELOPMENT IN PROBABILISTIC SOFTWARE TOOLS

The general-purpose UNIfied Probabilistic Assessment Software System, *UNIPASS*™, can be utilized independently, as a stand-alone software engine, and/or integrated with deterministic software tools to perform complex probabilistic analyses. In the analysis, *UNIPASS*™ provides the basis for modeling uncertainties, developing probabilistic process models, computing probabilities, identifying most likely outcomes, providing sensitivity data, identifying key drivers, analyzing risk, and performing sensitivity analysis, while the deterministic software tools may be integrated to provide the computational framework for constructing complex deterministic models.

To ensure predictive accuracy, *UNIPASS*™ provides multiple algorithms, which the user can select. By comparing the results of several algorithms, a level of confidence in the predictions can be achieved. Furthermore, *UNIPASS*™, in addition to 11 gradient-based MPP identification methods, also provides a robust simulation-based search algorithm that identifies MPPs for discontinuous and/or non-differentiable limit-sate functions.

UNIPASS Probabilistic Engine Provides Unmatched Capabilities for Performing Complex Probabilistic Analysis

- User friendly graphical user interface
- UNIX and Windows 95, 98, 2000, and NT operating systems
- 23 distribution types for modeling 4 classes of random variables including user-defined distribution
- 59 mathematical functions for modeling any complex event
  - Event model may be function of any variable or any previously defined function
- 3 analysis types including probability analysis, inverse probability analysis, and CDF/PDF analysis
- 4 different problem types including component, serial system, parallel system, and general system
- Numerous probabilistic methods in 6 categories for performing probabilistic analysis including FORM, SORM, SM, ISM, RSM, MVBM
- Generic and Customized Interfaces for easy integration with in-house and commercial codes
- Interface with MSC/NASTRAN finite element code

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Figure 21

LATEST DEVELOPMENT IN PROBABILISTIC SOFTWARE TOOLS

The probabilistic analysis begins by constructing process models and the probability distribution models. In addition to physic-based models, analysts often seek to construct models of processes, such as manufacturing processes, for which only some statistical data is available, and to construct These process models and probability distribution models can be constructed using our proprietary software tools *ProModeler*™ and *ProFi*™, respectively, utilizing available data. Using a general Bayesian framework, *ProModeler*™ constructs the process models utilizing available data. This tool provides a framework for the analysis of uncertainties and model assessment by a Bayesian Updating Rule. Utilizing available data, *ProFit*™ identifies the best probability distribution model using a combination of the maximum likelihood method, three goodness-of-fit tests, and probability paper approach. The method of maximum likelihood involves taking as the estimate for each unknown parameter the value that appears most probable on the basis of the given data. The goodness-of-fit tests are objective techniques that provide a probabilistic framework in which it evaluates the adequacy of the distribution function. Probability paper approach is more a subjective method that determines whether or not the data contradict the assumed model based on a visual examination. This concept can provide a great deal of useful information in addition to an evaluation of the appropriateness of the chosen model.

ProFit and _ProModeler_ Software
Provide Capabilities for Variable and Process Modeling

- ***ProFit*** engine identifies the best distribution type for a given data set
  - Identifies best distribution for a given data set comparing 22 distribution types
  - Performs 3 different goodness-of-fit tests
  - Provides probability paper
  - Estimates distribution parameters using method of moments and maximum likelihood method
- ***ProModele***r Provide several techniques for building the process model and identifying patterns from given data using
  - Last-square method, regression approach, and Bayesian updating

Unipass Technologies

Figure 22

Probabilistic System Design: Issues and Challenges

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PROBABILISTIC SYSTEM DESIGN

Probabilistic system design holds many opportunities to improve the total design process from concept to detailed design to service performance. Probabilistic design provides a rational basis for the linking of all of the interactive elements of system performance in a direct manner that accounts for the variability or uncertainties in all of the variables. However, there are major issues and challenges that yet must be overcome. The goal today is to provide an overview of the current state of probabilistic design while pointing the achievable work yet to be done.

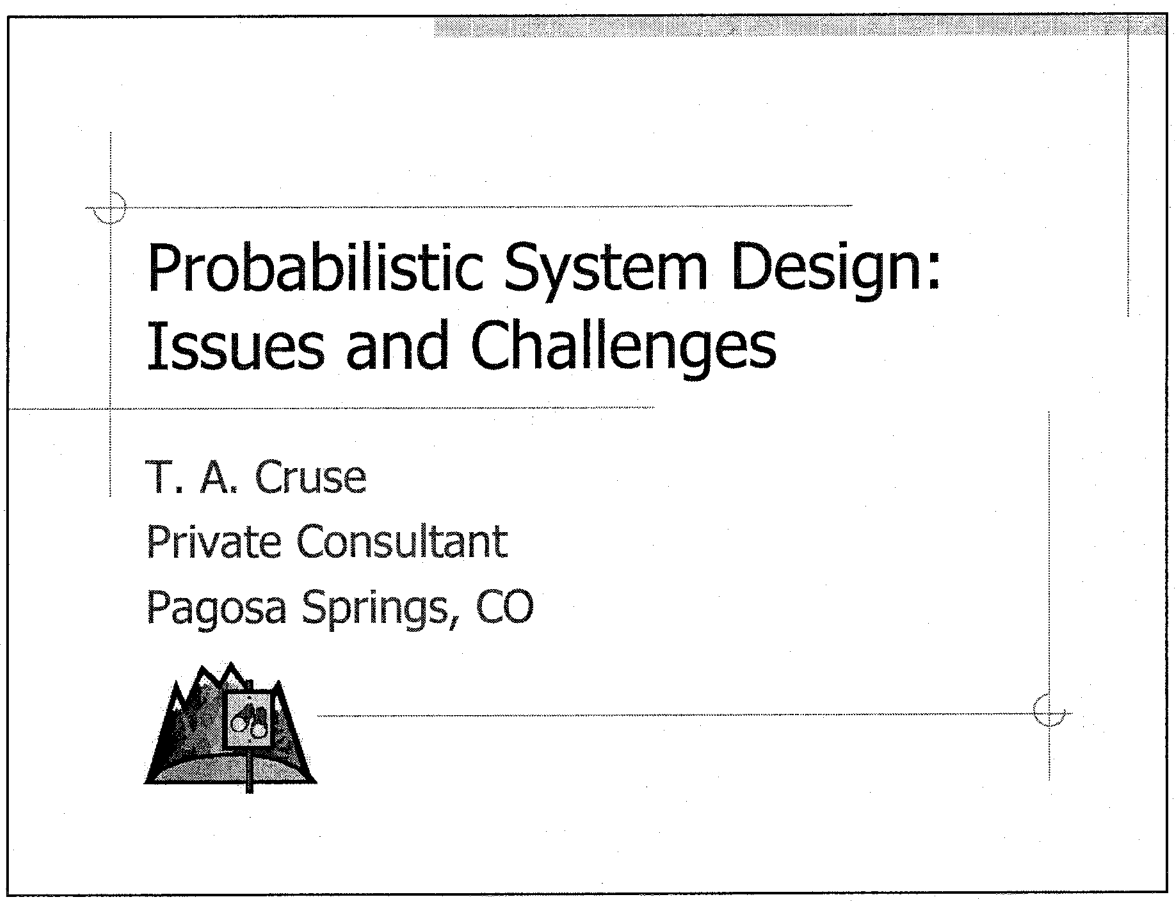

Figure 1

THREE MAIN MESSAGES

The reality today is the probabilistic methods are already finding their way into the design process in various industries. The revolution in the design process is already underway. The presentation will also address the message that probabilistic methods are not yet ready to deploy to the design floor to support the certification of advanced, man-rated systems. Finally, the presentation will address ideas on the integration of probabilistic methods with some non-traditional methods (at least to those doing design).

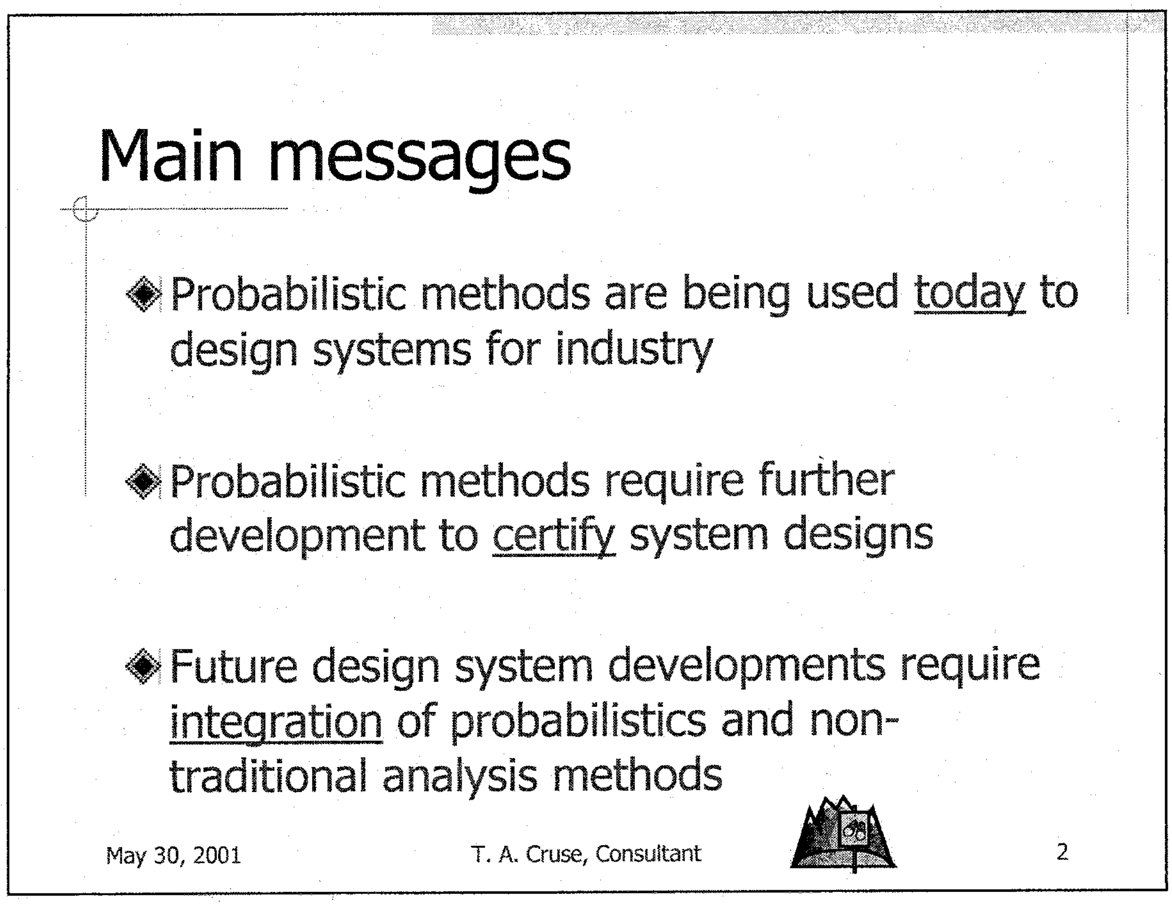

Figure 2

PRESENTATION OUTLINE

Probabilistic methods are not just research. They have already been deployed to industry to support product design as well as process engineering, with great savings in cost. The joint AF/Navy JSF program has committed to probabilistic high cycle fatigue design requirements as the required technology to assure product performance and reliability. The presentation also includes reference to a study done by this consultant for the NASA Glenn Research Center as part of the now-defunct NASA ISE program.

However, the basic tools and methods used in probabilistic design still require significant improvements in order to adequately support the design process for advanced aerospace systems. The key issues and challenges that remain included robustness and error bounds for all algorithms, the ability to predict confidence (or assurance) bounds on the predicted system outcome, and model verification and validation methods.

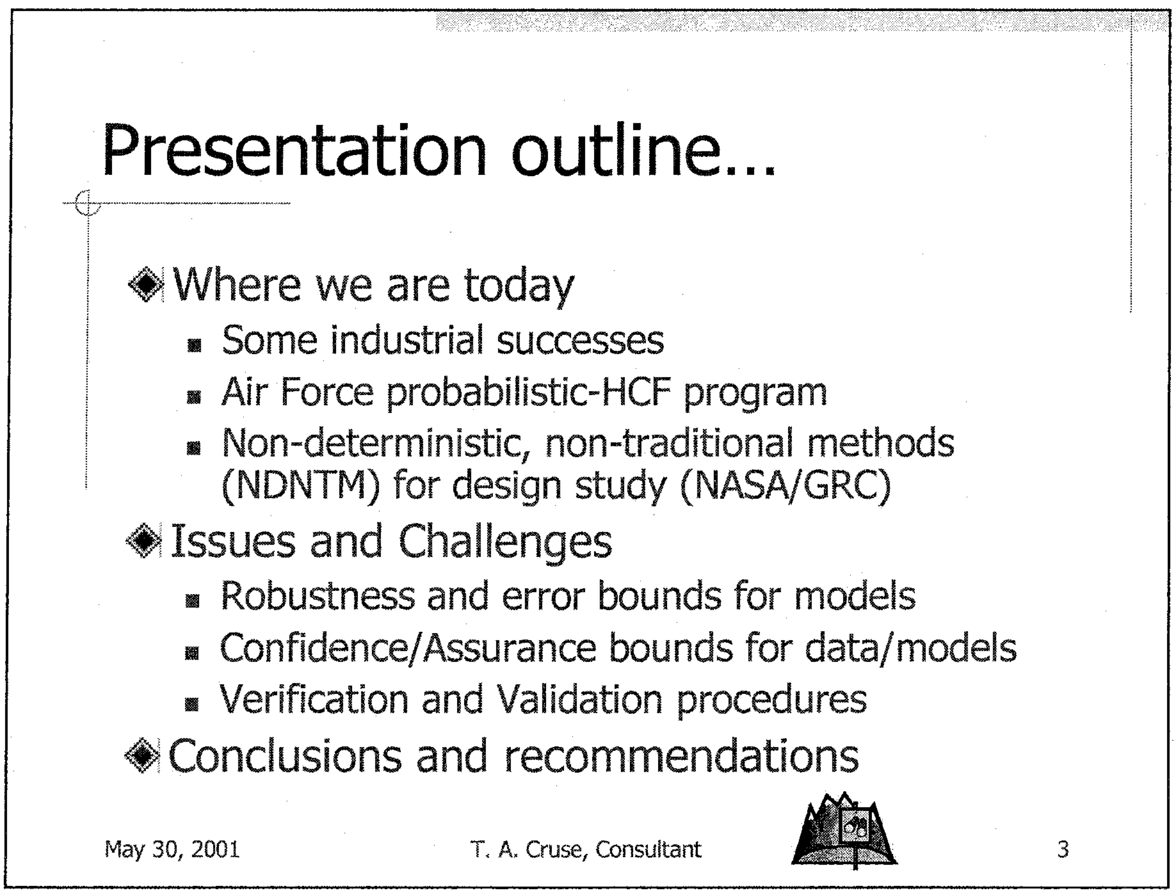

Figure 3

PREDICTIVE RELIABILITY ENGINEERING

Working with the Los Alamos National Laboratory, Delphi Automotive has deployed the PREDICT system that uses a probabilistic network approach to support the performance-based, reliability growth design process from concept to field deployment. Probabilistic modeling of the manufacturing processes at Procter and Gamble, also using LANL developed technologies, identifies processing improvements that achieve bottom-line benefits. That effort has been so successful that P&G is now marketing the technology to others. References are given to some of these keys, recent applications of technologies developed at Los Alamos National Laboratory. The technologies were developed to support the nation's weapons reliability requirements where analysis must substitute for full-scale testing.

Anon., "Proctor & Gamble starts peddling a "top secret" manufacturing technology," *Manufacturing News,* Vol. 8, No. 6, pp. 1, 6-8, Friday, March 30, 2001.

Kerscher, W. J., Booker, J. M., Bement, T. R., and Meyer, M. A., "Characterizing reliability in a product/process design assurance program," Los Alamos National Lab Report LA-UR-97-4072, Proceedings of the International Symposium on Product Quality & Integrity, Jan. 19-22, 1998, Anaheim, CA.

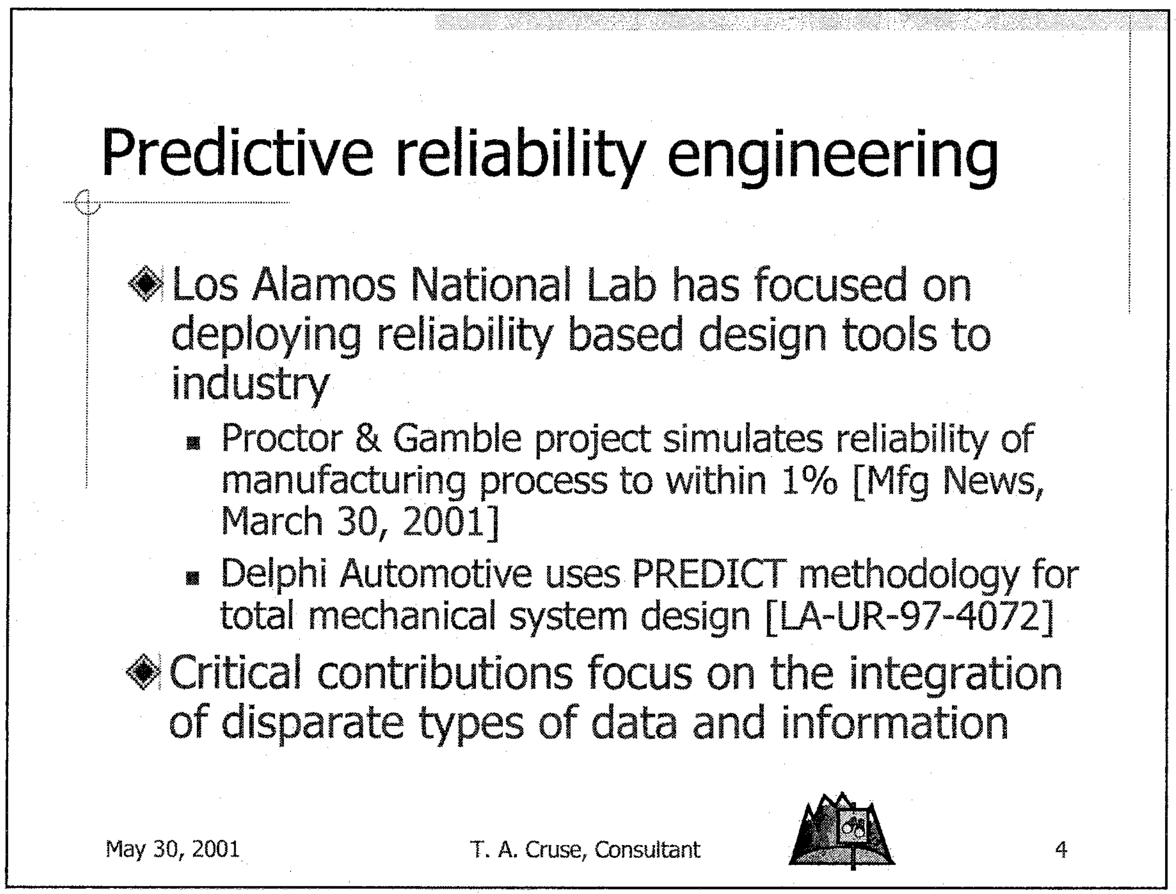

Figure 4

LANL PREDICT METHODOLOGY OVERVIEW

The PREDICT system has as its operating core the prediction of system performance (e.g., reliability) from conceptual design through field deployment. While the application to Delphi Automotive focused on reliability growth during the design and deployment process, aerospace design typically starts with a "successful" design on paper that meets the reliability goal but at a level of excessive weight, or other performance shortfall. The point is that predictions are made and tracked throughout the design process. Further, the range of uncertainty on the performance metric is identified and tracked along with its principal drivers. The goal is to increase reliability while decreasing the uncertainty range on that reliability. The PREDICT system tracks the metrics along with the drivers so that development and test investments are made where they can have the greatest impact on improved design.

As a normal part of the design process, the reliability may be adversely changed as the result of new information or data. That new information is fed into the Bayesian network to provide rigorous updates to the system performance. The critical technology to me in the LANL effort is the ability to integrate disparate forms of design and experimental information from expert opinion to test data.

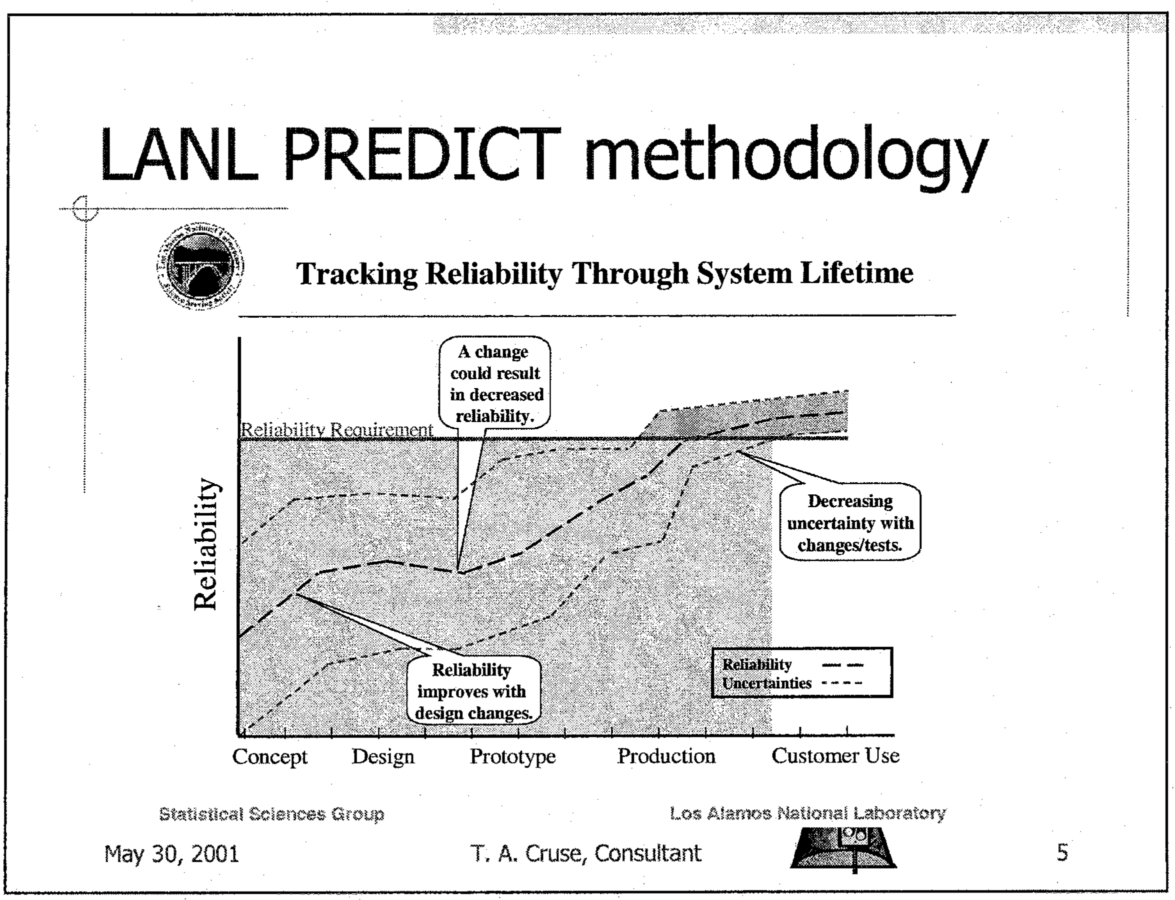

Figure 5

AF PROBABILISTIC HCF PROGRAM

The JSF turbine engine designs use integrally bladed rotors whose lightweight and flexibility means that dynamic modes are fully coupled across and around the rotor. Such dynamic coupling can result in "tuned absorber" dynamic response such that all energy feeds into a small region resulting in rapid structural failure. Deterministic design methods have been found to be incapable of controlling this phenomena and the commitment has been made by industry to step up to a full probabilistic design that links to manufacturing variability.

HCF design has been a major AF field failure problem for over two decades. Rotor LCF has largely been controlled through the damage tolerance design approach but HCF technology has lagged. The controlling design requirements for all engine structures is defined by the Engine Structural Integrity Program (ENSIP) guidelines contained in Mil-Std-1783A. That standard is now being updated to include probabilistics. The zeroth level change that has been accepted by industry is a probabilistic resonant frequency avoidance criteria.

The AF has joined with NASA to continue what had started as a NASA ISE program to infuse some of the LANL PREDICT technology into the AF HCF program. In particular, the effort is demonstrating how to elicit design and operating information from industry on the sources of and nature of the variability in the aeromechanics drivers and structural response for bladed rotor HCF failures.

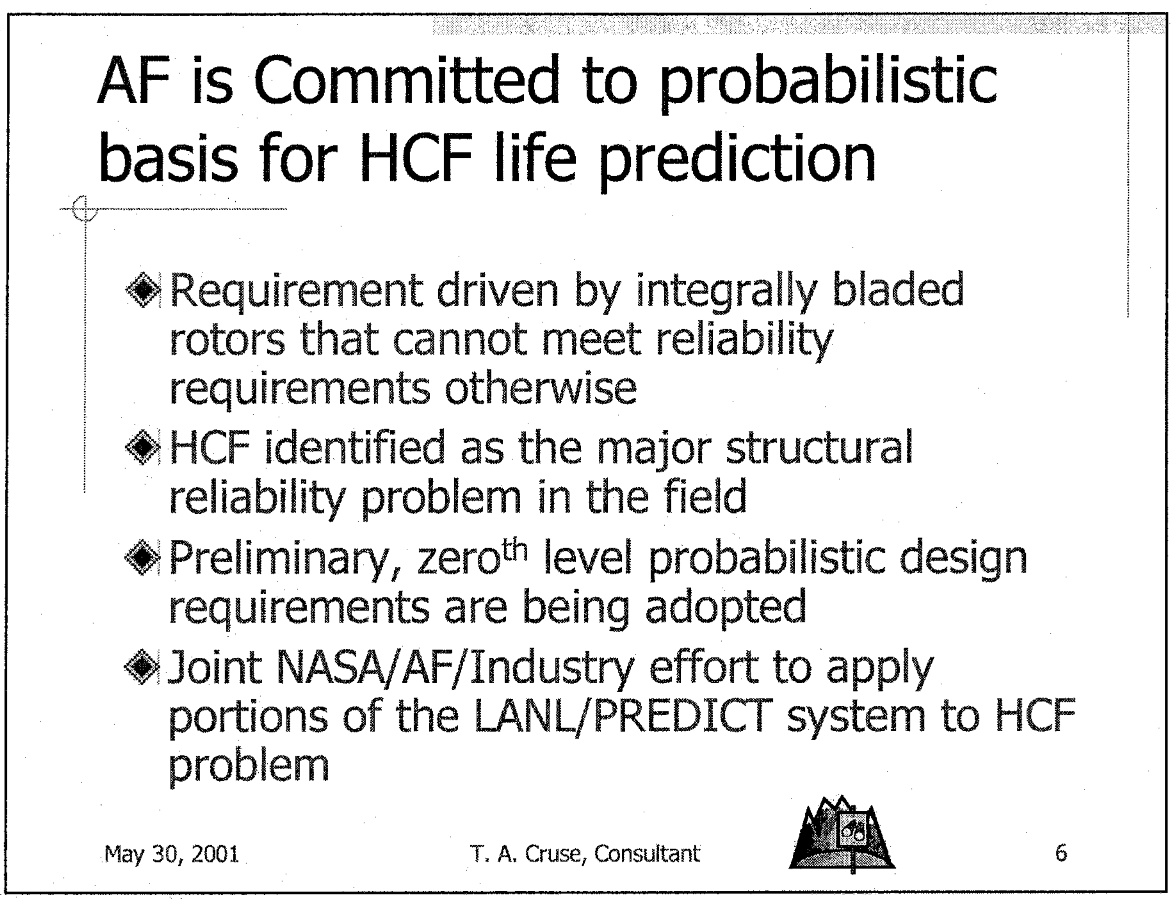

Figure 6

NASA/GRC ISE-FUNDED STUDY OF NDNTM FOR SYSTEMS DESIGN

This funded study was performed in CY 2000 and a final report is available through the Program Manager, Dr. C. C. Chamis. The context for the study undertaken by this consultant is the AF HCF program, the Consultant's experience and work in probabilistic design, a comprehensive literature review, and a personal belief that NDNTMs are required for the next generation space access vehicle system design. The study included a review of NASA's design technology base, current design environment studies in industry, and technology capabilities and efforts at a number of key small business or university sites.

The conclusion of the study is that we have no real current need for new probabilistic methods but that we have many important tasks to complete in order to deploy non-deterministic design into aerospace vehicle design practice. Another key conclusion reached by this consultant is that the nation lacks the critical leadership necessary to achieve a truly inter-operable, information based design environment such as envisioned by the NASA ISE effort. At this time it appears that every major aerospace firm is working on its own vision for such systems and these are not likely to work together.

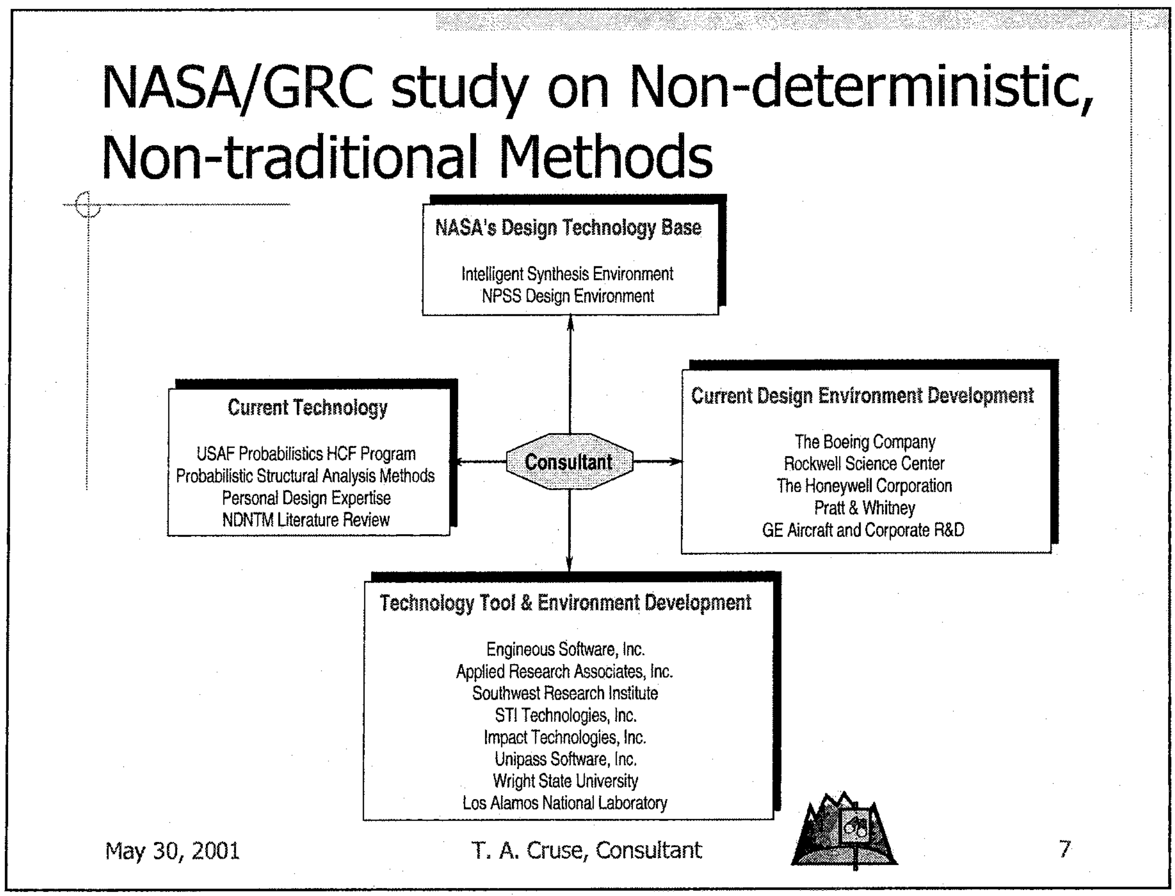

Figure 7

NDNTM STUDY PUBLISHED KEY RECOMMENDATIONS

The conclusion of my NDNTM study for NASA was that the future space access systems designs must integrate design information in innovative ways that include the variability and uncertainty issues upon which probabilistic design methods focus. The design environment is fundamentally driven by the need to integrate disparate forms of information from data to judgment. The design environment also requires the ability to work with many interoperable tools that might be generated by diverse sources and integrated at the desktop. The study proposed an integrated non-deterministic design environment.

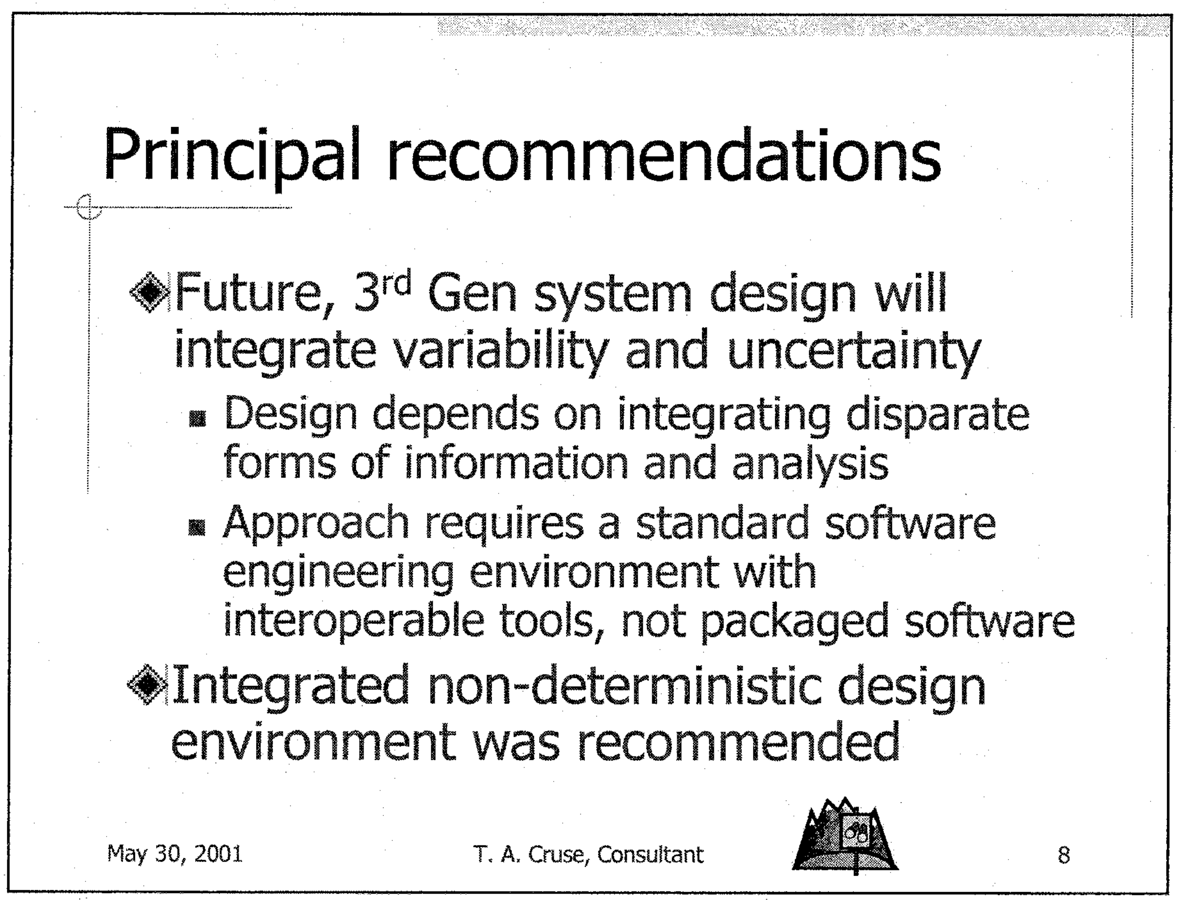

Figure 8

The focus in this graphic is on non-deterministic design using non-traditional methods. The chart shows in blue ovals the technology areas for which details are proposed in the NDNTM Final Report. Elements include intelligent interfaces, Bayesian networks, fuzzy logic for data/information fusion, and other non-traditional technologies. However, the central processing element of the NDNTM is mathematically rigorous probabilistic methods. Such algorithms as fuzzy logic were not found to be suitable or appropriate for the core analysis algorithms.

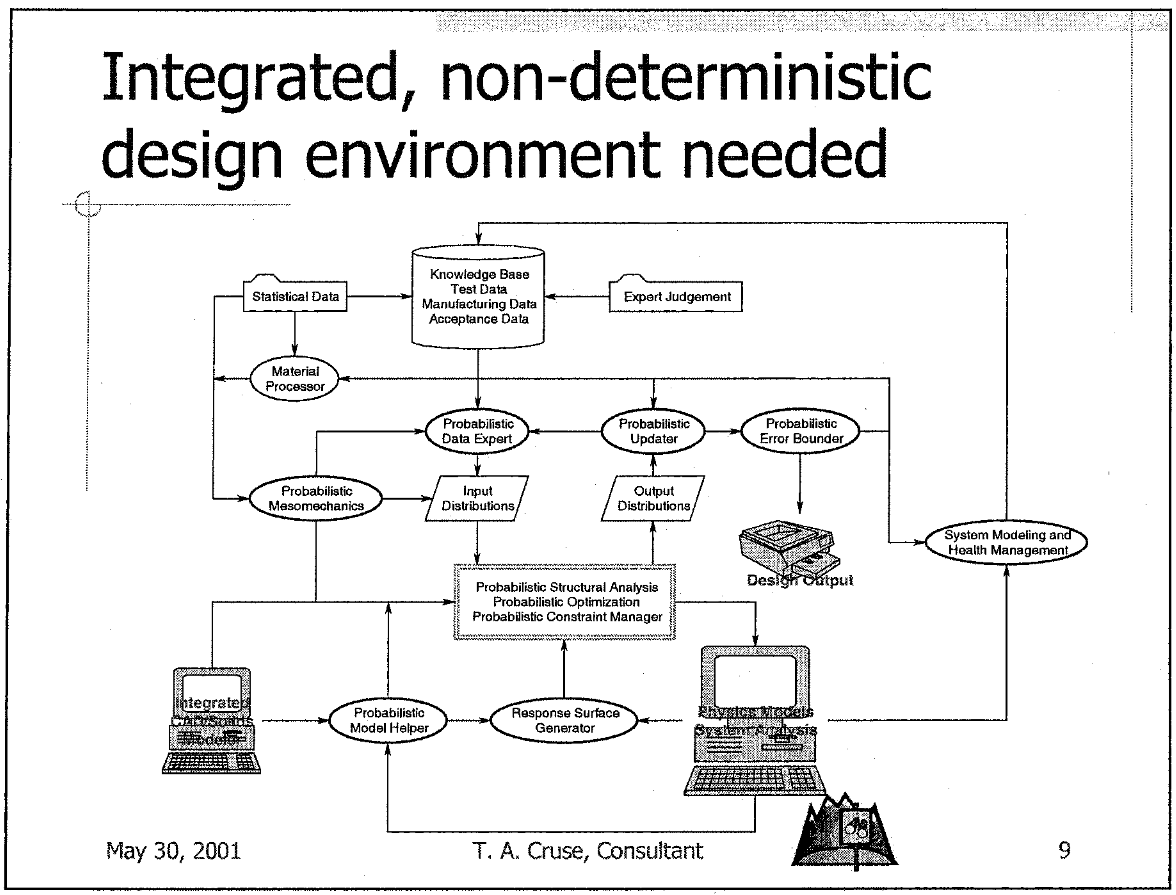

Figure 9

SIGNIFICANT CHALLENGES REMAIN

The current technologies used in probabilistic design appear to meet the design environment requirements in terms of basic capabilities. However, these methods lack the necessary robustness to be deployed to the design floor. Fast probability methods fail to converge for certain problem formulations, the output predictions have unstated or unknown accuracy, and the methods still require that the users be probabilistic experts.

The future design environment for advanced aerospace systems will involve many types of data and information to be integrated into the prediction system. The effective approach is to more fully utilize expert systems and their knowledge bases to provide interfaces to the tools, to assist in data preparation, and to provide "error traps" for complex modeling. Reliability networks are needed to represent the overall system being designed, to provide "what-if" modeling capability, to provide weighting functions for decisions on development investments, and to rigorously support reliability updating as new information is obtained. A critical need is to have the ability to merge soft data (engineering judgment) along with crisp data (e.g., experimental data) in rational ways that minimizes bias while fully retaining evaluative links to the data sources.

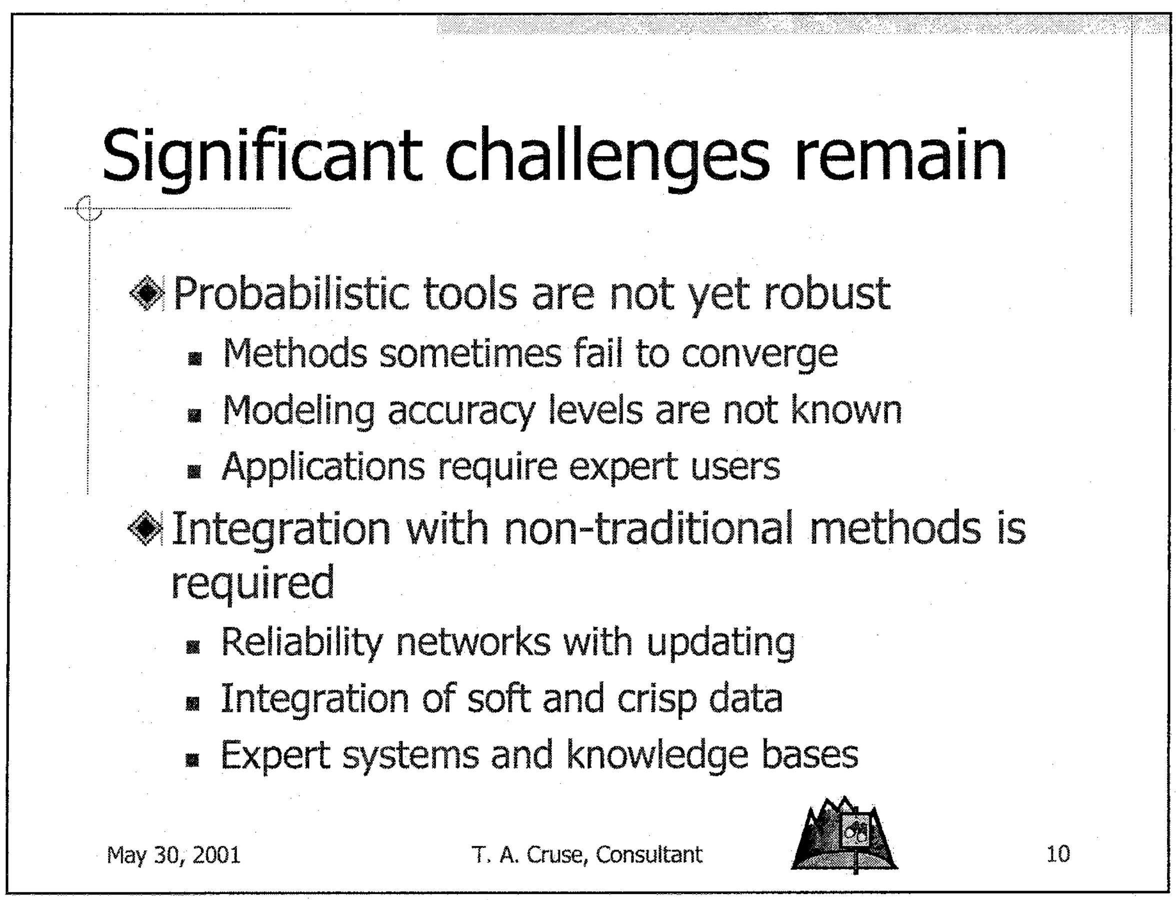

Figure 10

FAST PROBABILITY ALGORITHM ROBUSTNESS TESTED

As part of the AF HCF program, the Consultant applied some of the standard fast probability integrations, as provided by Southwest Research Institute, to a simple 1D oscillator design problem posed by GE Aircraft Engines (GEAE). The 1D model was sharply peaked in the form of the shown limit state. A mathematically equivalent form of the same limit state can be derived that is essentially an inverse of the shown state. That equivalent form did not have the indicated problems in computing predicted reliabilities.

The GEAE problem had seven random design variables. They derived eight design cases that had differing nominal conditions for each of the seven variables. Using a design of experiments (DOE) approach, GEAE determined values of the design variables for each design case that had low probabilities of failure (third column). The Monte Carlo method was used with different numbers of simulations (second column) to make what were taken to be converged reliability predictions. The remaining three columns show the Advanced Mean Value Plus (with iterations), First Order Reliability Method, and Second Order Reliability Method predictions. In the form of the peaked response model of the 1D system, each of the methods failed for one or more of the DOE cases. The problems are not associated with the so-called multiple-limit state problem for fast methods. Rather, they seem to be purely numerical problems associated with a poorly resolved limit state.

$$\left[\left(\frac{Y}{100}\right)\cdot LFMSF\cdot\left[\frac{\dfrac{1}{\sqrt{\left[1-\left[\dfrac{m\cdot\frac{N}{60}}{\left[\omega_{NN}+S\cdot\left(N-N_{Nom}\right)\right]}\right]^2\right]^2+\left[2\cdot\xi\cdot\dfrac{m\cdot\frac{N}{60}}{\left[\omega_{NN}+S\cdot\left(N-N_{Nom}\right)\right]}\right]^2}}}{D_{Nom}}\right]\cdot\left(\frac{\rho_{Allow.Nom}}{\rho_{Allow}}\right)\right]-1=0$$

- Strongly-peaked response function form for limit state
- The limit state form resulted in poorer numerical behavior
- Problem is similar to what occurs in numerical optimization algorithms

DOE Case	N_sims	MC (TAC)	AMV+	FORM	SORM
2	600K	0.00017	0.00016	0.0000	~10^-26
4	200K	0.00763	0.00764	~10^-32	~10^-42
6	600K	0.00059	0.00059	0.0000	0.0000
8	200K	0.01440	0.99980	~10^-25	0.0000
10	600K	0.00369	0.00356	0.00309	0.0037
12	200K	0.03040	0.02940	0.99990	0.9999
14	200K	0.02448	0.02335	0.02200	0.0239
16	200K	0.08477	0.08210	0.07940	0.0834

May 30, 2001 T. A. Cruse, Consultant 11

Figure 11

SMART ENVIRONMENTS NEEDED

Some of the conclusions reached by the Consultant regarding the current probability integration algorithms are indicated. The fact is that fast methods are really faster than Monte Carlo. There is little doubt to this observer that fast methods will be needed for future aerospace systems design. However, their deployment will not be accepted until the shortcomings are rigorously addressed. Research sponsors and program managers must link the development of future tools to requirements that address these needs.

Monte Carlo methods will also be required. While typically taken to be "truth" there are significant capabilities that these methods must also contain in order to be used in this future design environment. The needed capabilities include the ability to capture the so-called probabilistic sensitivity factors that are critical to the design process. Such factors are used to narrow the problem space, to allocate information resources, and to compute confidence intervals. Monte Carlo methods must also have their own automated simulation error controls that adaptively adjust the simulation numbers to the outcome probability of failure results.

All methods used must make modeling error bound estimates for each problem. The error bounds are required to support system certification and to compute confidence interval estimates.

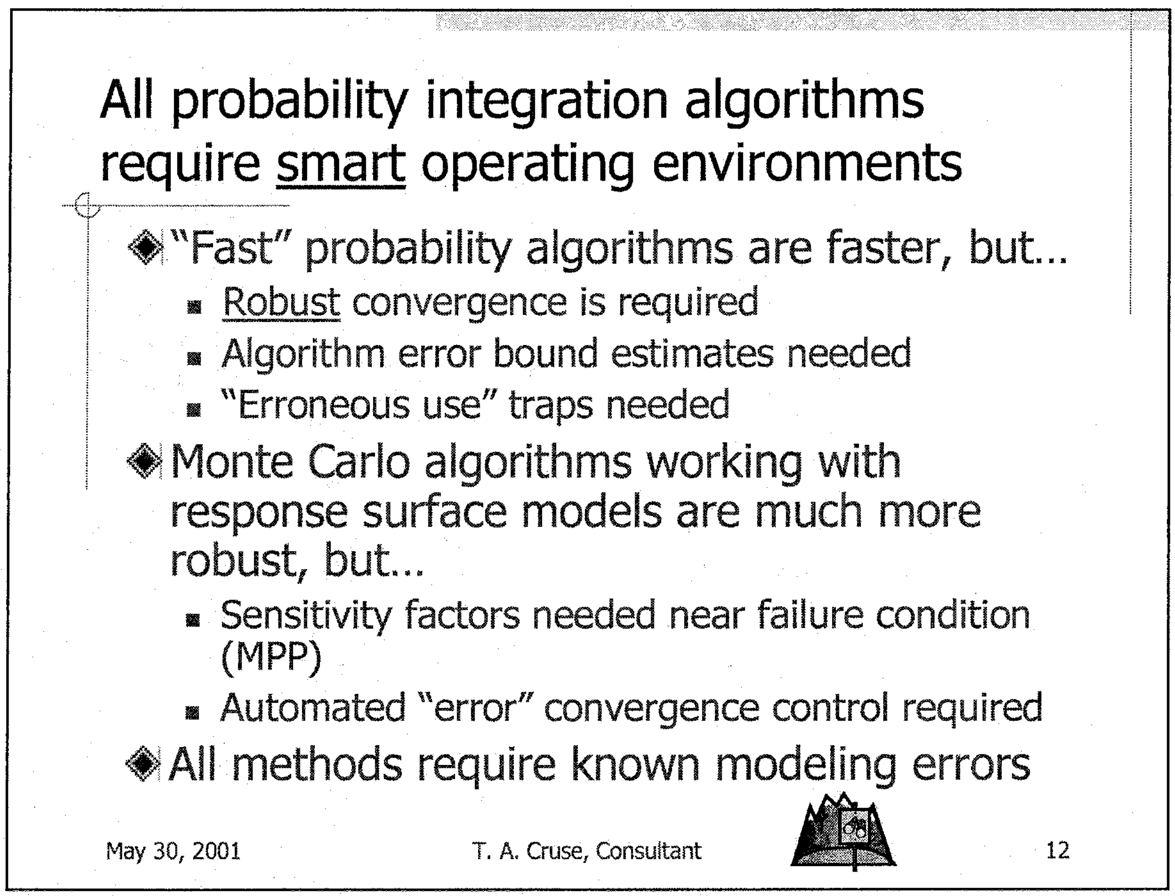

Figure 12

CONFIDENCE INTERVALS ARE REQUIRED

Classical statistical confidence intervals are mathematically linked to the quantity of experimental data. As such, statistical confidence intervals are not appropriate to the future NDNTM design environment. The fact is that aerospace vehicle design, as opposed to electronic device manufacturing, cannot be evaluated by replicated system failure testing! Yet, confidence intervals are still required – we need to be able to answer the question of "how good is our estimate?"

Bayesian (belief) networks are the effective mathematical means for computing engineering confidence intervals (as opposed to statistical confidence intervals). Some would call these intervals assurance intervals to make the distinction clearer but the word "confidence" appears to be the most meaningful to engineers. Bayesian networks allow many kinds of answers to the indicated questions to be integrated in estimating the range of outcomes.

Certainly, the key issues addressed in the Verification and Validation process for analysis methods also contribute to making such confidence or assurance estimates.

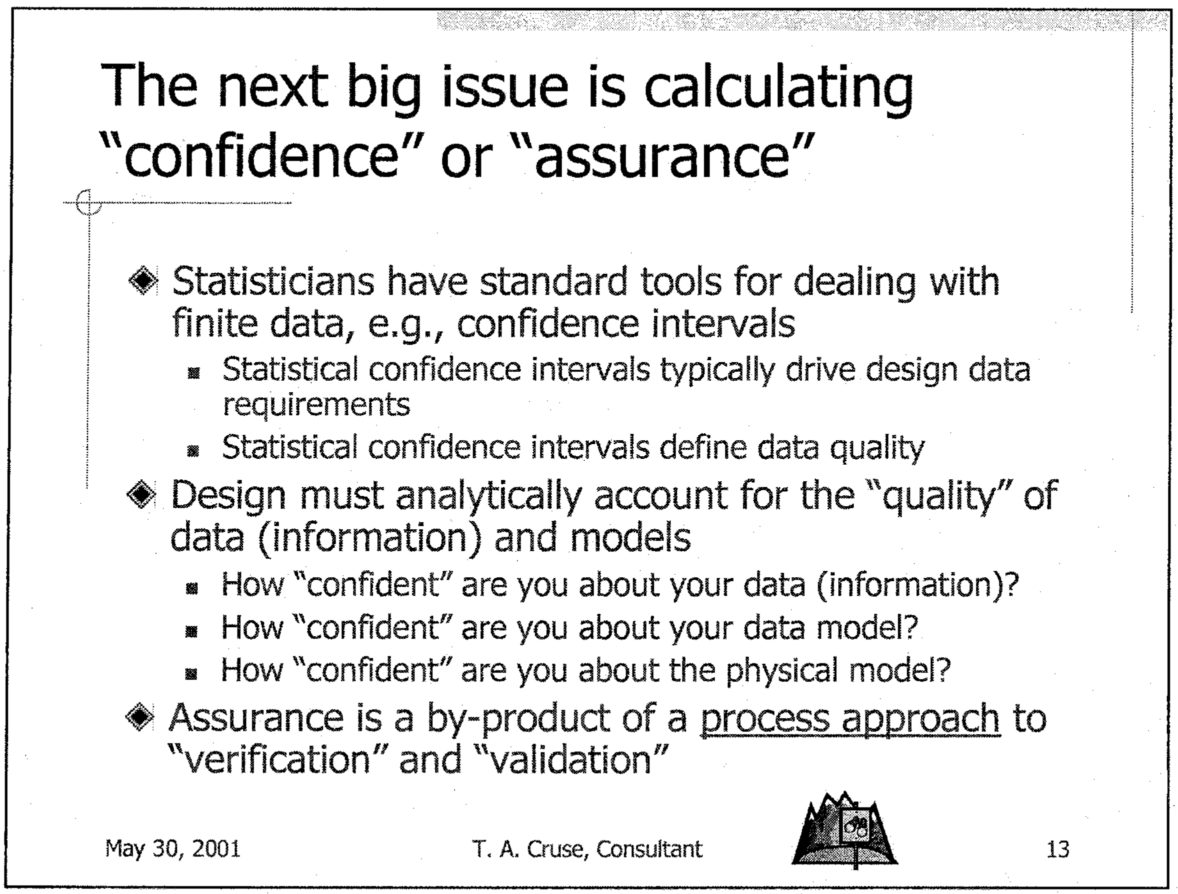

Figure 13

As a simple example, I illustrate the effect of uncertainty on the seven input distributions used for the GEAE 1D oscillator test problem. Again, I acknowledge the support of SwRI through the use of their Nessus code to make these calculations. The algorithm is base on outer "do loops" of Monte Carlo simulations that account for the variability in the input variables.

In each case shown, each random design variable's distribution parameters, the mean and the standard deviation, was assumed to have a uniform distribution. The "width" of the uncertainty, or its interval, was defined by the coefficient of variation of that parameter. Two cases were taken where the mean and standard deviation had intervals of 5%, 10% respectively, and 0.5%, 1.0% respectively. The results are stated in terms of the two-sided (upper and lower bounds) for the predicted probability of failure of 0.0144. That is, how large (or small) might the probability of failure be if we don't have perfect information on the input variables? The simulations do not include the effect of modeling errors!

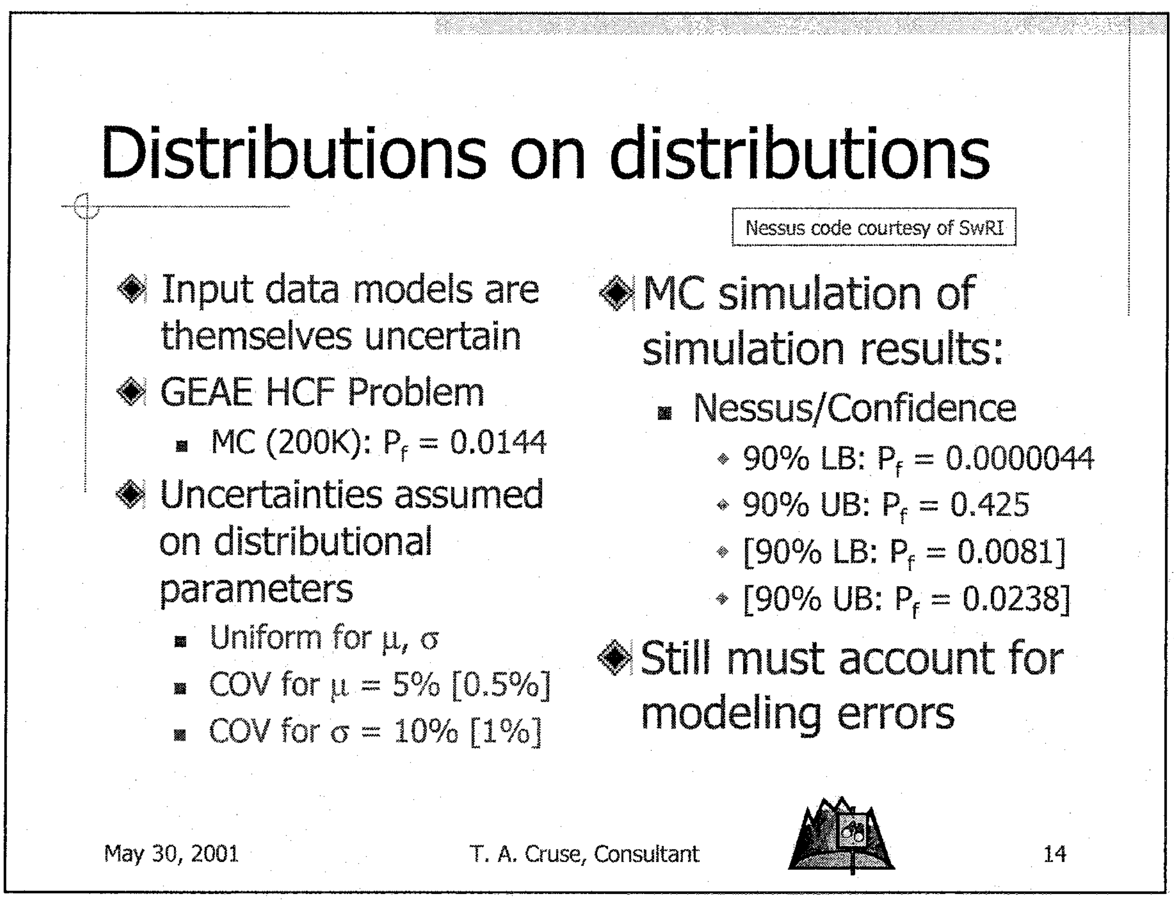

Figure 14

Design analysis methods themselves have uncertainties. Verification addresses whether or not the computational methods that are used accurately represent the assumed model. Validation addresses whether or not the model accurately represents the underlying physics that is being modeled. Both steps are critical.

System certification addresses both the process and the outcome. An example is the FAA certification of the design of critical rotating parts in commercial aircraft turbine engines. The certification process requires a complete verification and validation of the tools used – deterministic tools today – to certify the safe life predictions for these critical engine components.

I am certain that such verification and validation requirements will exist for the NASA space access program. Such methods are now being developed in detail for the national nuclear weapons certification program. The AIAA has published a V&V guide for CFD while the ASME has just approved a code committee action for finite element programs. No such effort currently exists for probabilistic methods.

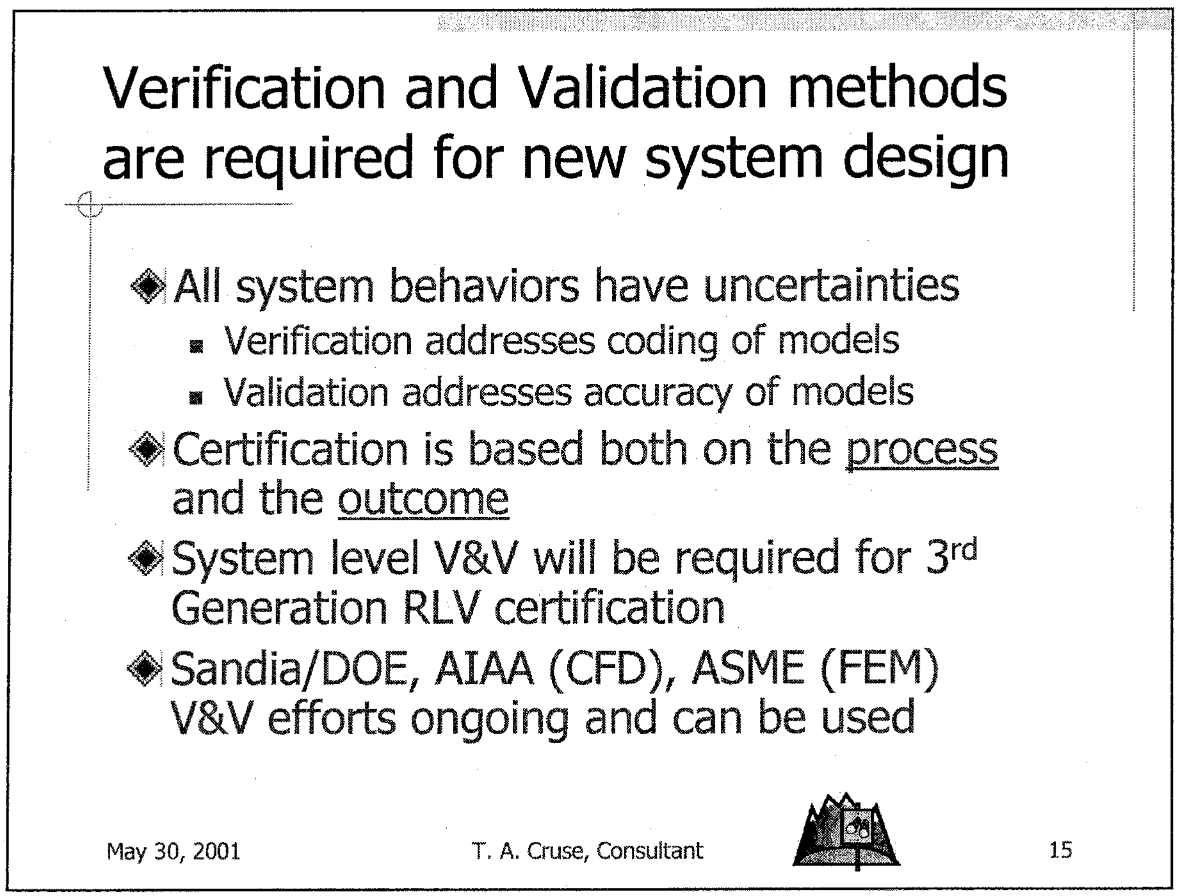

Figure 15

CONCLUSIONS

Probabilistic design is not some future thing. It is here today. It is the right approach to some of the most critical design issues of risk-based decision making, cost reduction, and testing. However, the design environment needs real work to be done in order to meet the needs of certifying complex aerospace systems. Finally, system certification must include work on the verification and validation of the probabilistic methods that we will use. NASA Program Managers are in a position to address many of these needs in their future research procurements.

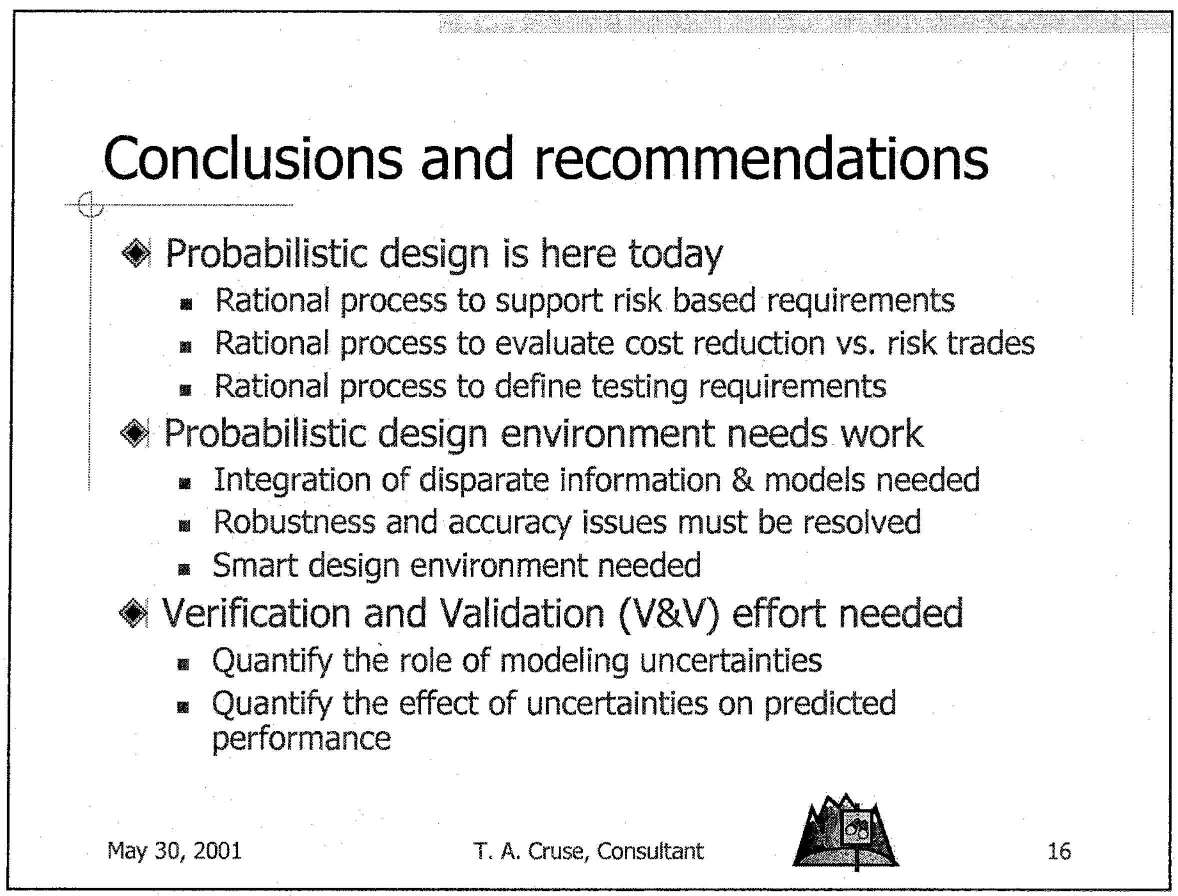

Figure 16

Applications of Nondeterministic Methods on Vehicle Conceptual Design

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Applications of Non-Deterministic Methods on Vehicle Conceptual Design

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Figure 1

Motivation

- Moving from deterministic design to robust/probabilistic design methods amounts to an admission that uncertainty exists *and* has a significant impact on system performance
- Want to *analytically* answer the questions: ⟹ **Probabilistic Design**
  - How much design margin is really necessary?
  - How do design parameters impact the uncertainty in performance?
  - What can be done to reduce this impact? ⟹ **Robust Design**
- Obstacles to implementation:
  - Organizational inertia
  - Lack of probabilistic analysis tool to bridge the gap between deterministic and probabilistic methods
  - Computational Costs, if not approached intelligently

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2

Figure 2

The Design Process Paradigm Shift

- A ***paradigm shift*** is underway that attempts to change the way complex systems are being designed
- Emphasis has shifted from design for performance at any cost to design for affordability
- There is a need for a multi-disciplinary approach to the problem based on more sophisticated higher fidelity tools
- Forecasting with a high probability of success the economic viability of the system in the early phases of design appears to be the key to success
- Due to the life cycle implications of this approach a need exists to create an environment that virtually designs, tests, certifies, manufactures, and operates the system, while accounting for design ambiguity, uncertainty and risk

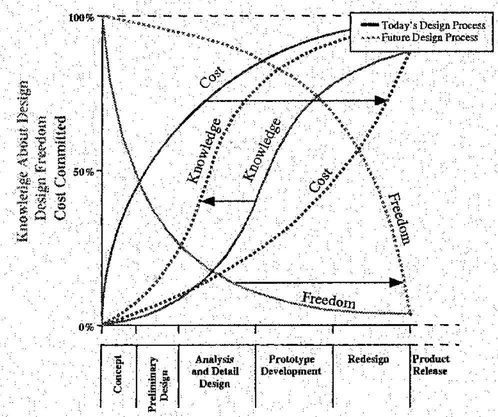

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Figure 3

Affordability- Making the Right Decisions Early

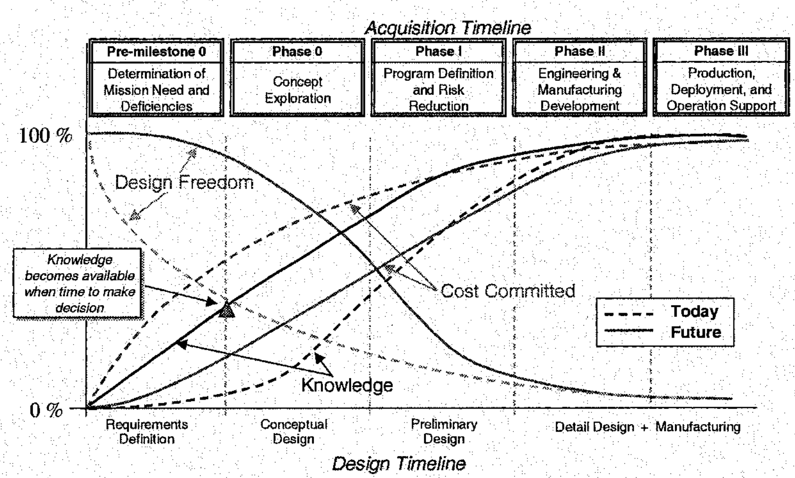

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Figure 4

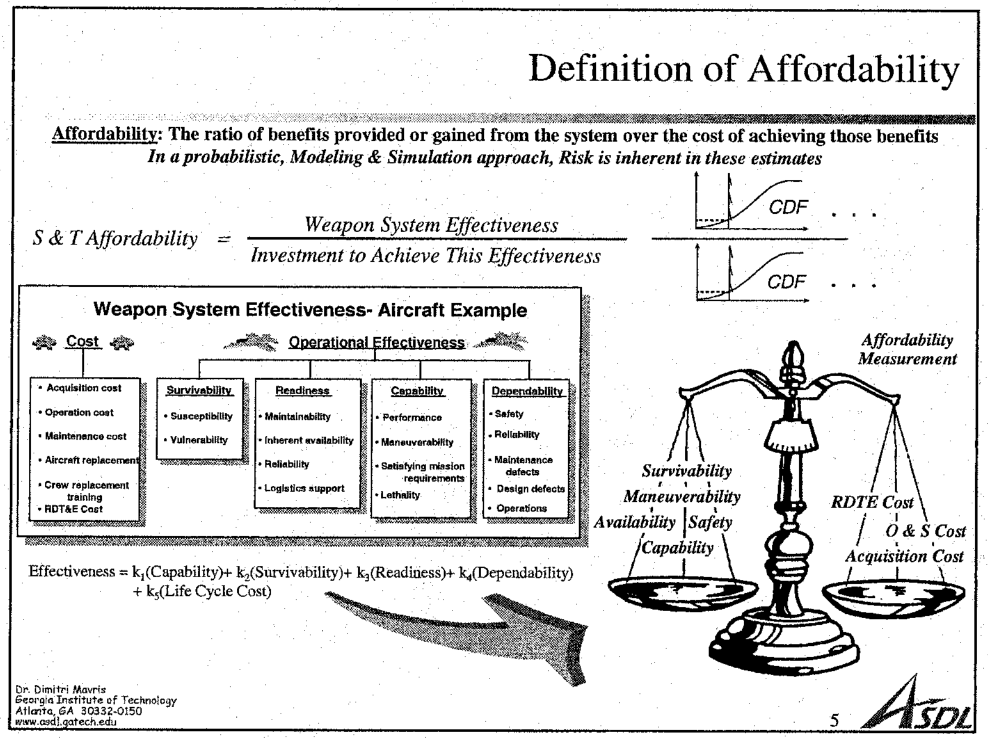


Figure 5

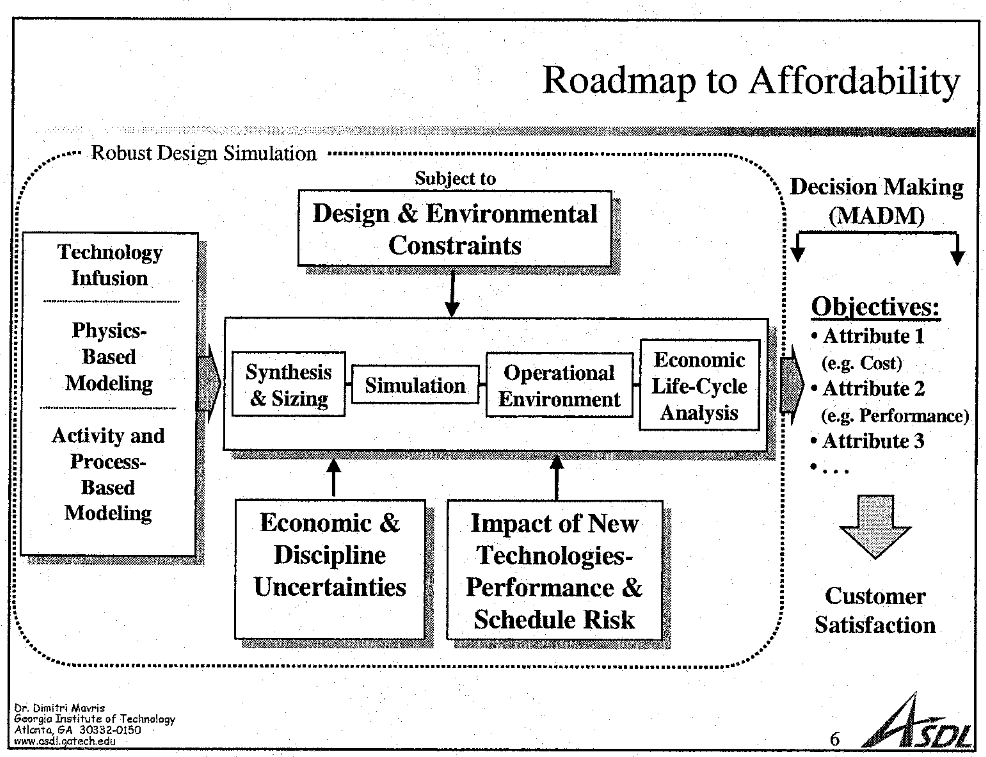


Figure 6

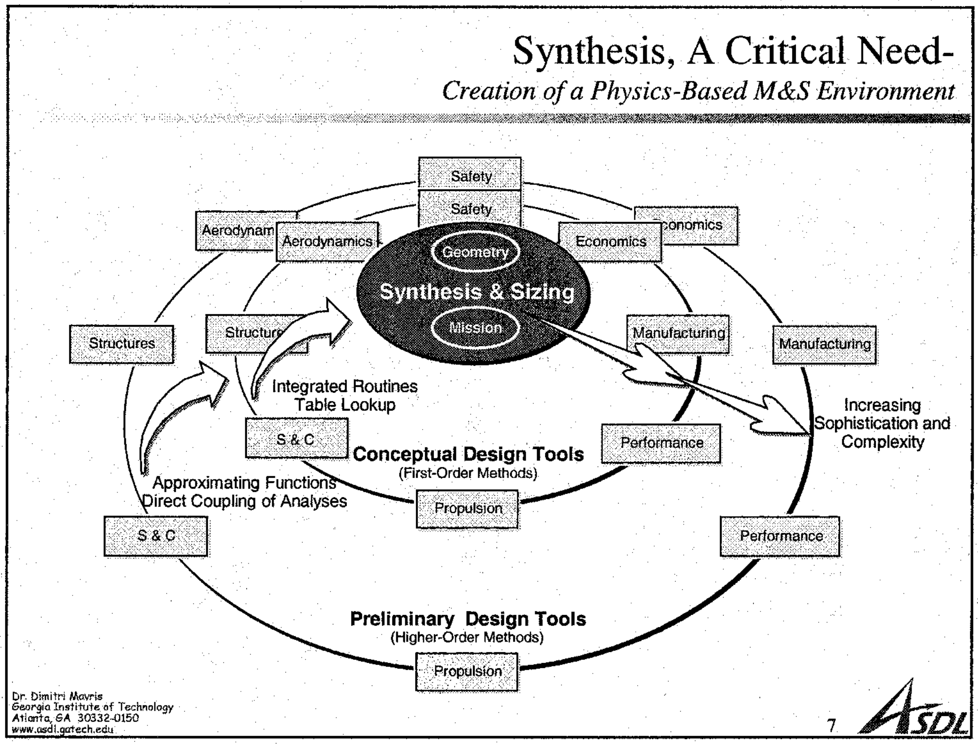


Figure 7

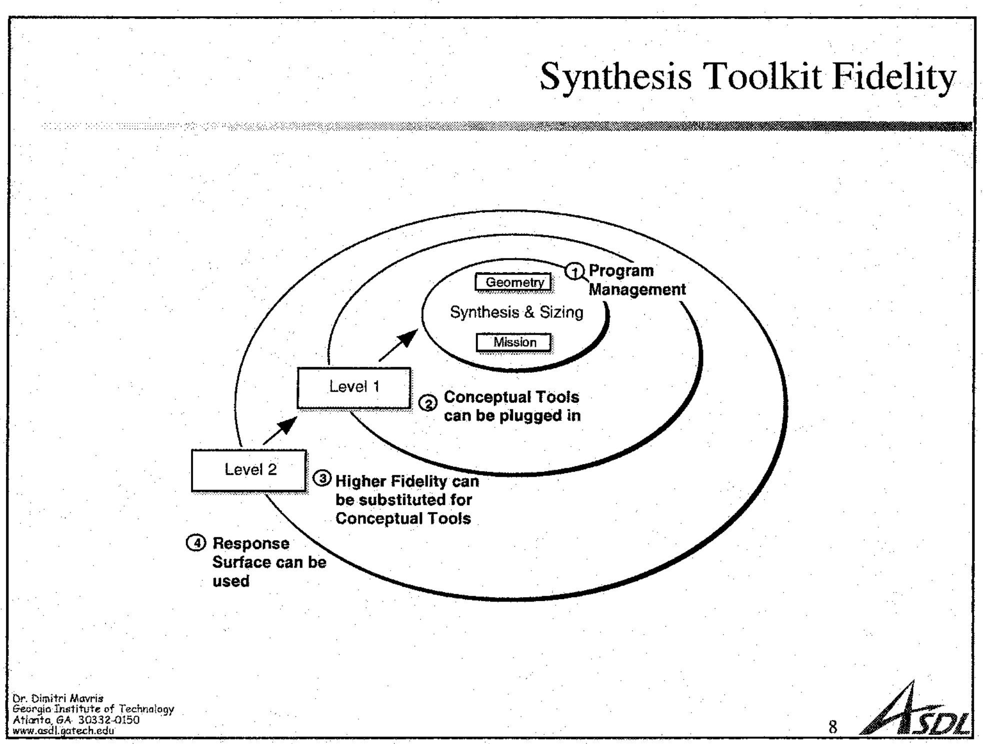
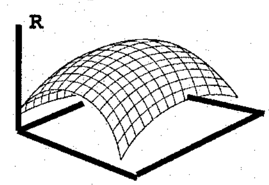


Figure 8

Response Surface Methodology (RSM)

- RSM is a multivariate regression technique developed to model the response of a complex system using a simplified equation
- Regression data is obtained intelligently through the Design of Experiments (DoE) techniques
- RSM is based on the design of experiments methodology which gives the maximum power for a given amount of experimental effort
- Typically, the response is modeled using a second-order quadratic equation of the form:

$$R = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j$$



Where,

b_i are regression coefficients for the first degree terms
b_{ii} are coefficients for the pure quadratic terms
b_{ij} are the coefficients for the cross-product terms

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Figure 9

Design of Experiments

Purpose: Minimize number of experiments required for desired level of resolution !

Design of Experiments	For 7 Variables	For 12 Variables	Equation
Full Factorial	2,187	531,441	3^n
Central Composite	143	4,121	2^n+2n+1
Box-Behnken	62	2,187	-
D-Optimal Design	36	91	(n+1)(n+2)/2

	Factors			
Run	X_1	X_2	X_3	**Response**
1	-1	-1	-1	y_1
2	+1	-1	-1	y_2
3	-1	+1	-1	y_3
4	+1	+1	-1	y_4
5	-1	-1	+1	y_5
6	+1	-1	+1	y_6
7	-1	+1	+1	y_7
8	+1	+1	+1	y_8

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Figure 10

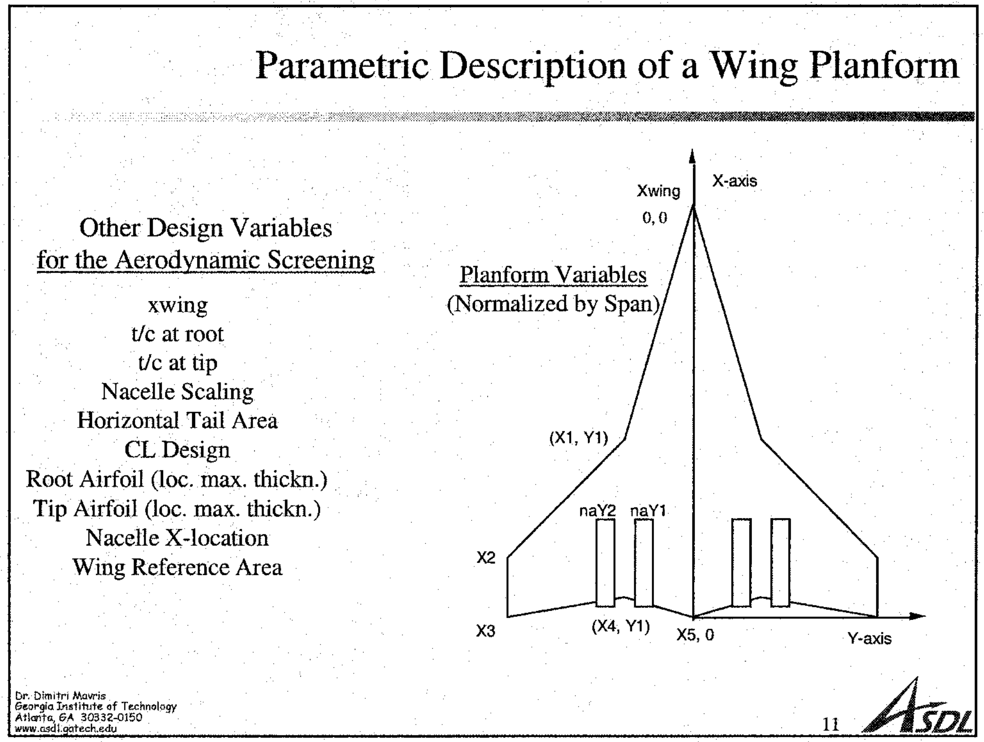

Figure 11

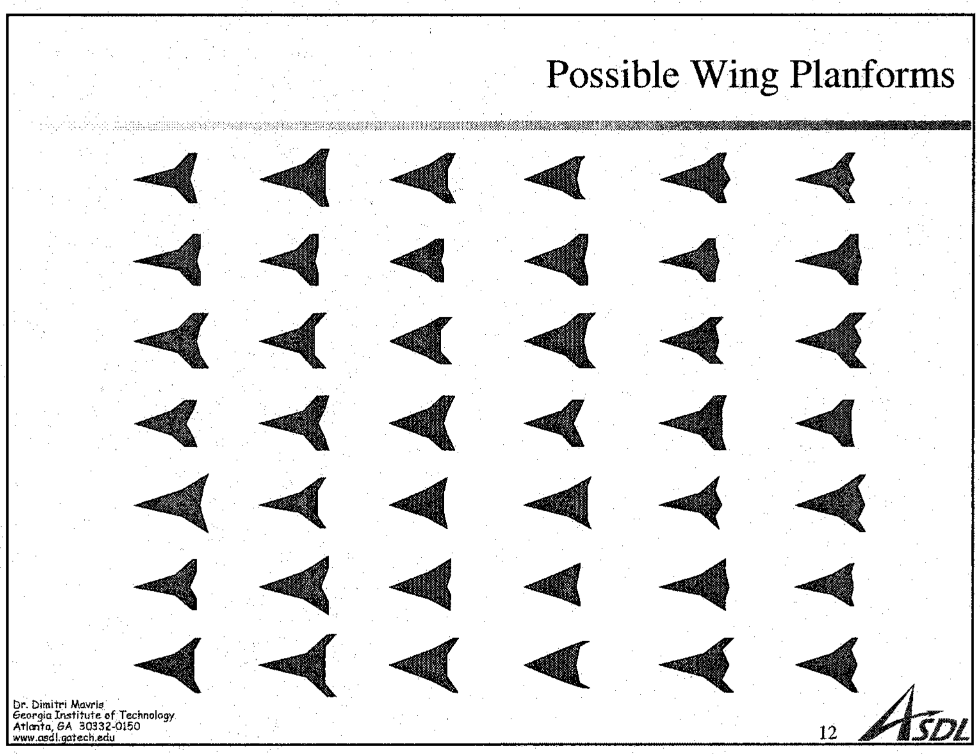

Figure 12

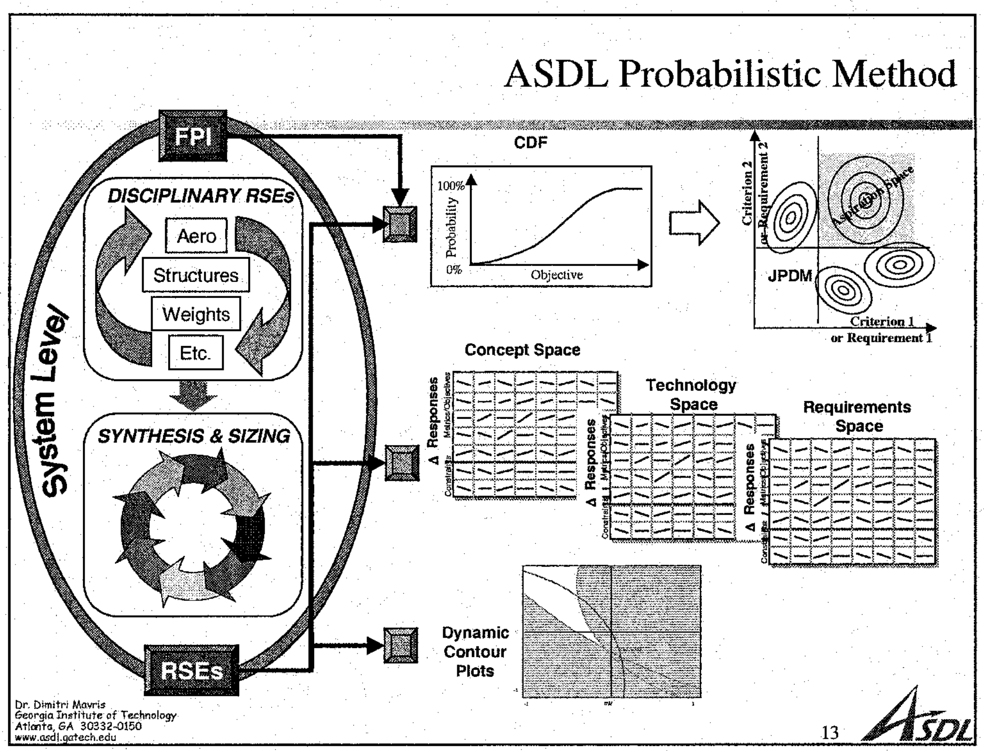

Figure 13

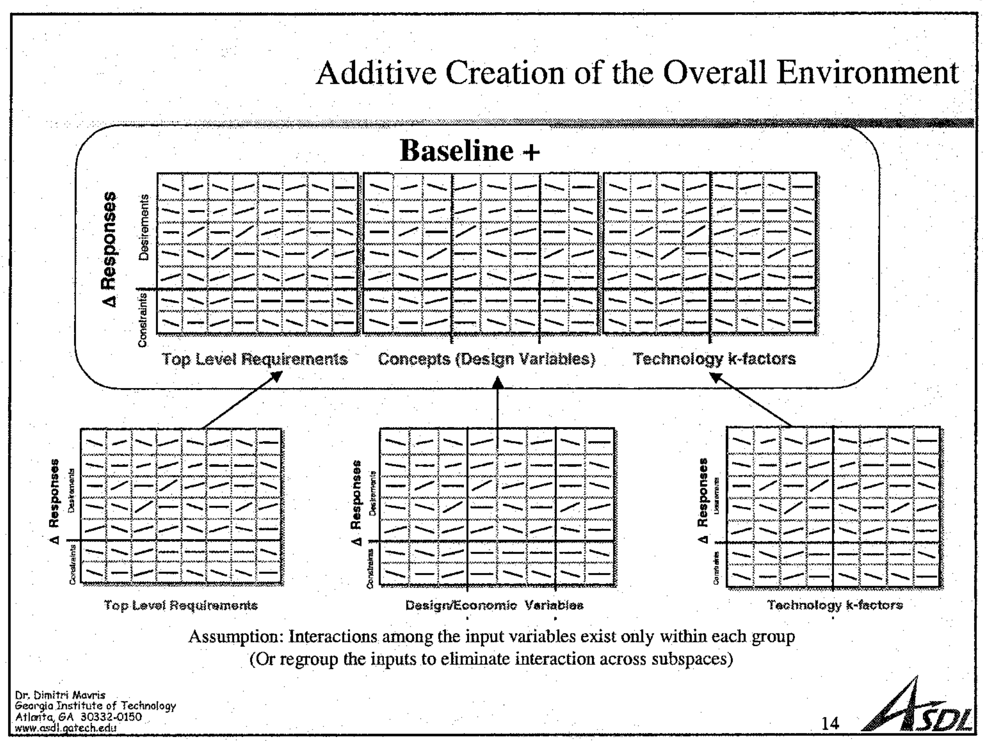

Figure 14

Options for Probabilistic Design

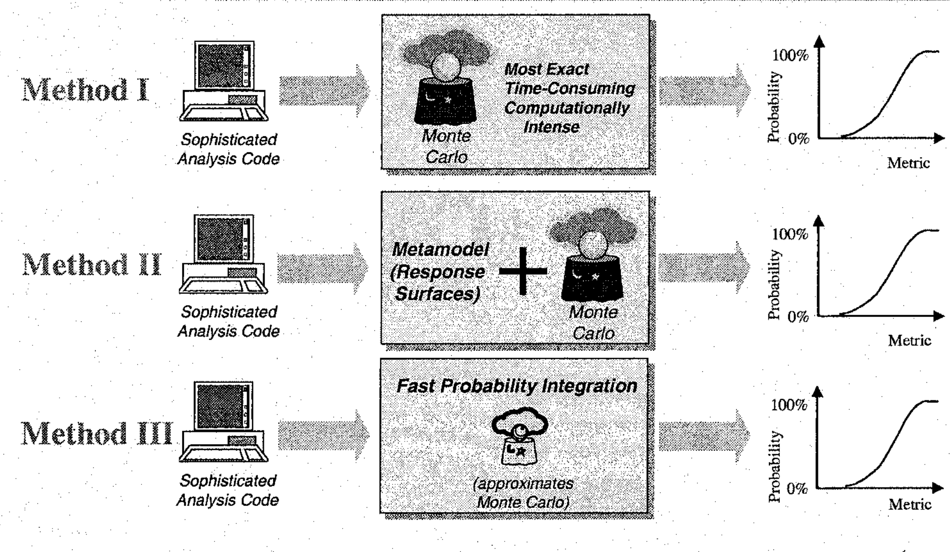

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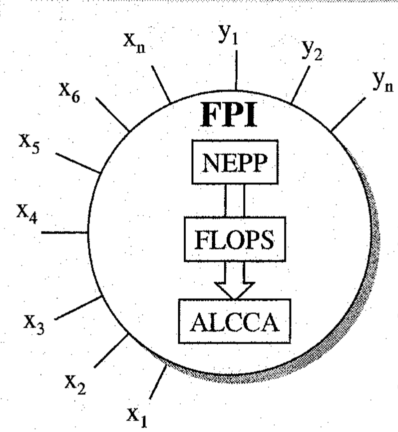
Figure 15

Fast Probability Integration (FPI)



- FPI manages program execution while handling up to 100 deterministic (x_i) or probabilistic (y_i) variables, with capability for expansion
- Establishes design feasibility
- Identification of most critical constraints
- Creates probabilistic sensitivity derivatives and CDFs for each objective & constraint
- Assessment of new technologies impact deterministically or probabilistically
- Probabilistic solutions for a set of design variables subject to uncertainty
- Identification of feasible and/or robust solutions, by assigning random distributions to each design variable, within the range of applicability, and allowing for operational and manufacturing uncertainty

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Figure 16

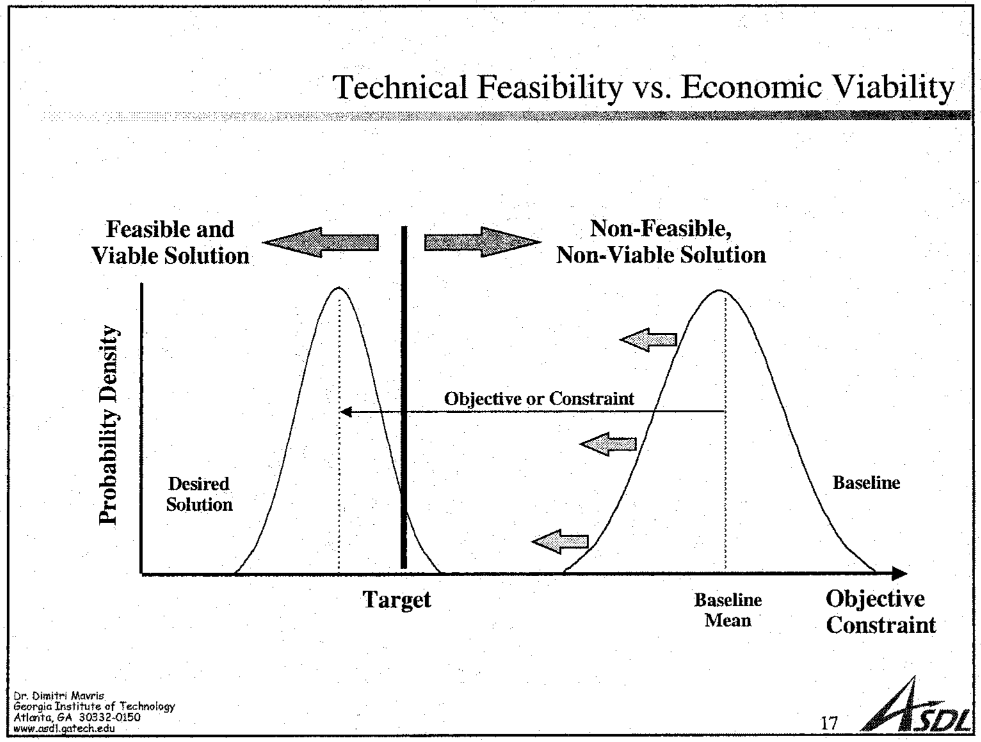

Figure 17

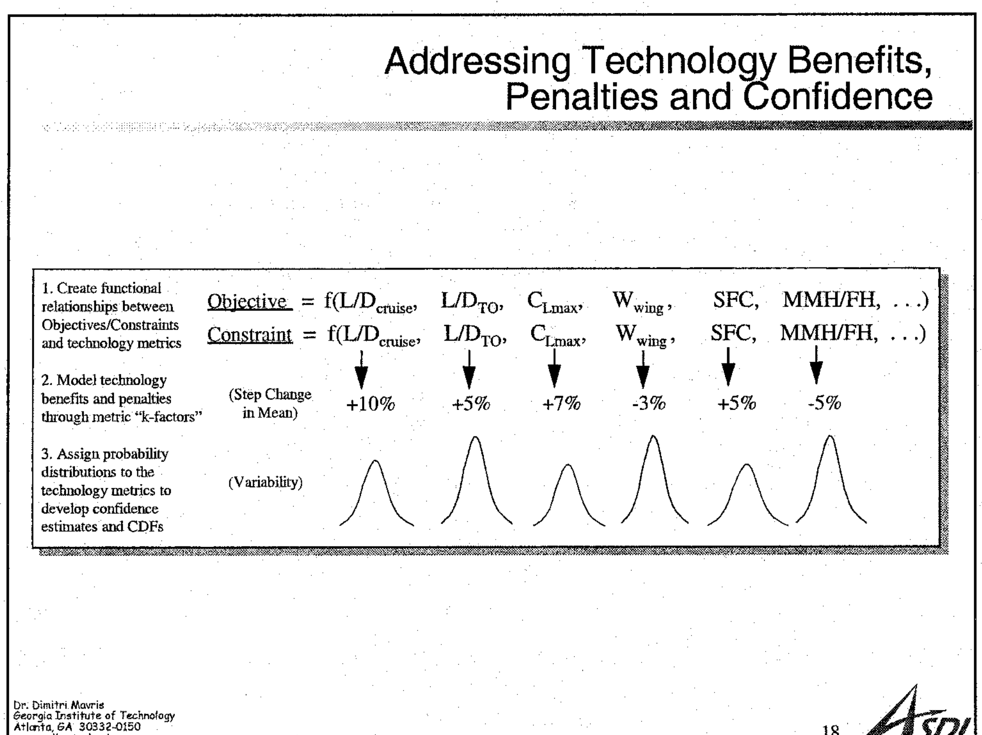

Figure 18

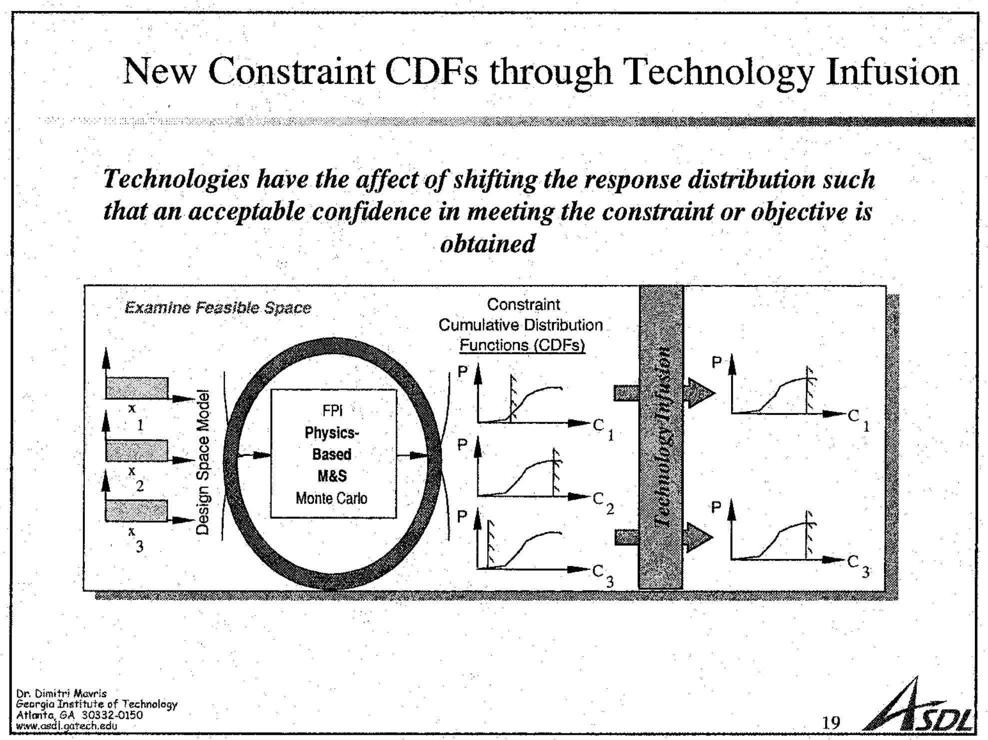

Figure 19

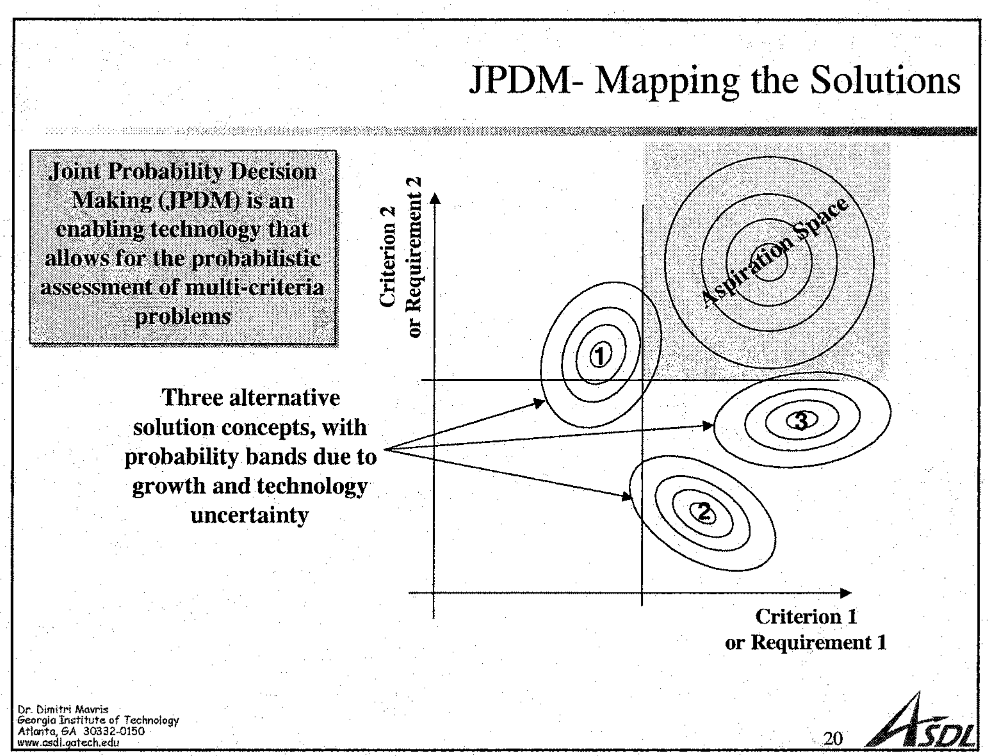

Figure 20

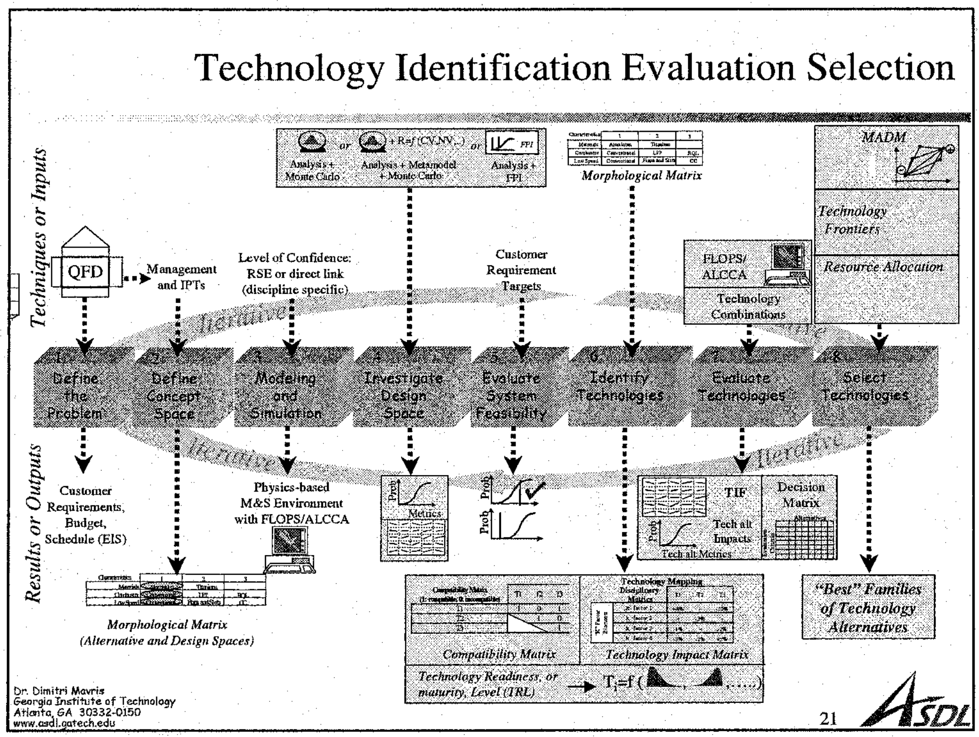
Technology Identification Evaluation Selection
Techniques or Inputs
QFD
Management and IPTs
Level of Confidence: RSE or direct link (discipline specific)
Analysis + Monte Carlo
Analysis + Metamodel + Monte Carlo
Analysis + FPI
Customer Requirement Targets
Morphological Matrix
FLOPS/ ALCCA
Technology Combinations
MADM
Technology Frontiers
Resource Allocation
Iterative
1. Define the Problem
2. Define Concept Space
3. Modeling and Simulation
4. Investigate Design Space
5. Evaluate System Feasibility
6. Identify Technologies
7. Evaluate Technologies
8. Select Technologies
Results or Outputs
Customer Requirements, Budget, Schedule (EIS)
Physics-based M&S Environment with FLOPS/ALCCA
Morphological Matrix (Alternative and Design Spaces)
Metrics
TIF
Tech alt Impacts
Tech alt Metrics
Decision Matrix
Compatibility Matrix
Technology Impact Matrix
Technology Readiness, or maturity, Level (TRL)
"Best" Families of Technology Alternatives
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Figure 21

EXAMPLE APPLICATION

The TIES method developed a few years ago in response to some very aggressive vehicle concepts that could not meet future performance or economic objects, especially with present day technologies or geometric perturbations. New technology infusion was the only option. Yet, the cost conscious industry was very concerned with investment cost and risk associated with developing and infusing new technologies that have a great deal of uncertainty. Thus, a means to quantify the impact in terms of performance, cost, and risk in the early phases of design was needed.

Hence, the Technology Identification, Evaluation, and Selection method was created.

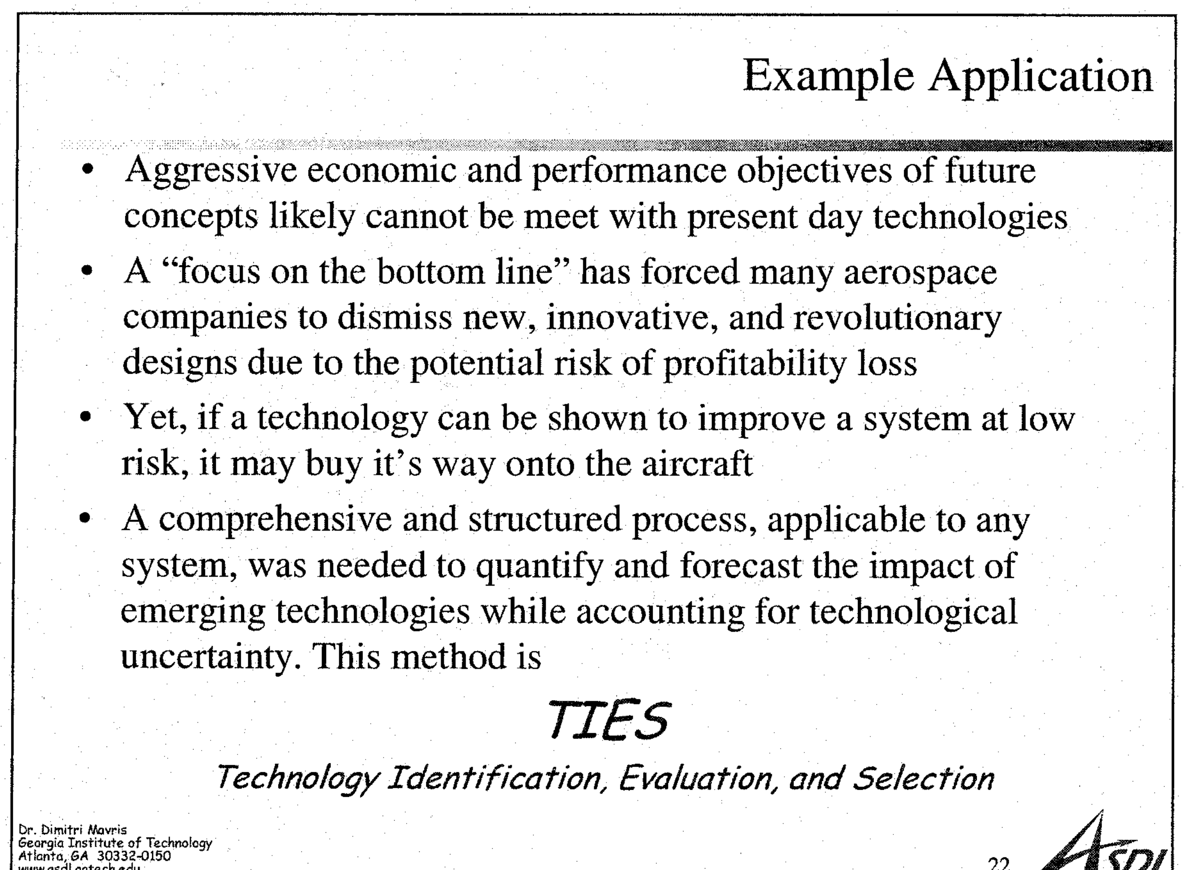

Figure 22

Problem Definition

Societal Need:

Desire for a next generation supersonic aircraft
Increased commercial traffic growth
Increased comfort, safety, and affordability

Potential Concept Class:

High Speed Civil Transport
(Concorde class derivative)

Design Requirements:

Through QFD and brainstorming exercises, the customer requirements were mapped to quantifiable engineering parameters

	Parameter	Target/ Constraint	Units
	Performance		
Technical Criteria	Approach Speed (V_{app})	≤ 155	kts
	FAR 36 Stage III Flyover Noise (FON)	≤ 106	EPNLdB
	Landing Field Length (Landing FL)	≤ 11,000	ft
	FAR 36 Stage III Sideline Noise (SLN)	≤ 103	EPNLdB
	Takeoff Field Length (TOFL)	≤ 11,000	ft
	Takeoff Gross Weight (TOGW)	≤ 1,000,000	lbs
	Economics		
Economic Criteria	Acquisition Price (Acq $)	*minimize*	FY96 $M
	Research, Development, Testing, and Evaluation Costs (RDT&E)	*minimize*	FY96 $M
	Average Required Yield per Revenue Passenger Mile ($/RPM)	≤ $ 0.10	FY96 $
	Total Airplane Related Operating Costs (TAROC)	*minimize*	FY96 $
	Direct Operating Cost plus Interest (DOC+I)	*minimize*	FY96 $

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Figure 23

DEFINE CONCEPT SPACE

With the requirements defined, a potential class of vehicles must be defined. A structured means of doing so is with a Morphological Matrix. The morphological matrix is nothing more than a decomposition of all possible contributing elements of the system. It is a means to brainstorm and think out of the box for potential solutions to the problem.

For example, the project manager could bring together all of his experts and decompose the system. Do we want a wing and tail vehicle? Or a wing and canard? And so on. If you do this for each element of the system, then you have effectively defined the alternative concept space which may have mission parameters, technologies, and so on.

Once this matrix is sufficiently defined, one must establish a baseline to continue on with the TIES method. You do this by selecting one element from each row like the circled items, usually present day capabilities. This is your baseline that you will do all deviations on.

Next, that system is further decomposed into geometric and propulsive parameters that will define the design space to be investigated for feasibility.

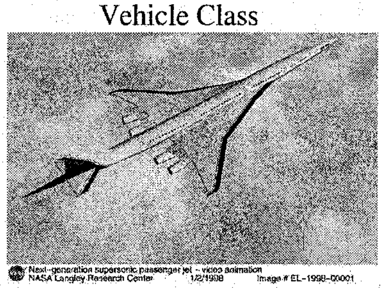
Define Concept Space:

Alternatives Space

Space of Alternatives

- Began with a Concorde-class aircraft and modified based on market studies
- Decomposed vehicle class into system characteristics and characteristic alternatives to define the component alternatives and potential technologies through a Morphological Matrix
- Baseline configuration (circled) established from the characteristic alternatives representative of present day capabilities
- Mission defined based on market requirements

Vehicle Class



Decompose

	Characteristics \ Alternatives	1	2	3	4
Config	Vehicle	Wing & Tail	Wing & Canard	Wing, Tail & Canard	Wing
	Fuselage	Cylindrical	Area Ruled	Oval	
	Pilot Visibility	Synthetic Vision	Conventional	Conventional & Nose Droop	
Mission	Range (nmi)	5000	6000	6500	
	Passengers	250	300	320	
	Mach Number	2	2.2	2.4	2.7
Propulsion	Type	MFTF	Turbine Bypass	Mid Tandem Fan	Flade
	Materials	Conventional	High T Comp		
	Combustor	Conventional	RQL	LPP	
	Nozzle	Conventional	Internal Flow Alteration	Mixed Ejector	Mixer Ejector & Acoustic Liner
Aero	Low Speed	Conventional Flaps	Conventional Flaps & Slots	C C	
	High Speed	Conventional	NLFC	Active Control	HLFC
Struct	Materials	Aluminum	Titanium	High Temp. Composite	
	Process	Integrally Stiffened	Spanwise Stiffened	Monocoque	Hybrid

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Figure 24

DEFINE CONCEPT SPACE: DESIGN SPACE

With the requirements defined, a potential class of vehicles must be defined. A structured means of doing so is with a Morphological Matrix. The morphological matrix is nothing more than a decomposition of all possible contributing elements of the system. It is a means to brainstorm and think out of the box for potential solutions to the problem.

For example, the project manager could bring together all of his experts and decompose the system. Do we want a wing and tail vehicle? Or a wing and canard? And so on. If you do this for each element of the system, then you have effectively defined the alternative concept space which may have mission parameters, technologies, and so on.

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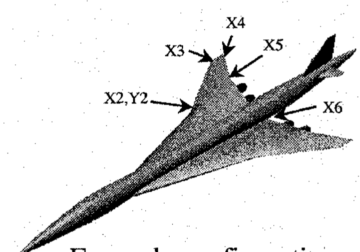
Next, that system is further decomposed into geometric and propulsive parameters that will define the design space to be investigated for feasibility.

Define Concept Space:

Design Space

<u>Design Space</u>

- Design space was defined with geometric and propulsive variables from a decomposition of baseline
- Ranges established to capture as many configurations as possible, from an arrow to a double-delta and push the state-of-the-art in propulsion capabilities
- Initial feasibility is sought within this space



Variable	Minimum	Maximum	Units	Description
SW	7500	9000	ft^2	Wing area
TWR	0.29	0.33	~	Thrust-to-weight ratio
TIT	3000	3400	°R	Turbine Inlet Temperature
FPR	3.5	4.5	~	Fan Pressure Ratio
OPR	18	21	~	Overall Pressure Ratio
CLdes	0.08	0.12	~	Design lift coefficient
X2	1.54	1.69	~	LE kink x-location*
X3	2.1	2.36	~	LE tip x-location*
X4	2.4	2.58	~	TE tip x-location*
X5	2.19	2.37	~	TE kink x-location*
X6	2.18	2.5	~	TE root x-location*
Y2	0.44	0.58	~	LE kink y-location*
t/c_root	3	5	%	Wing root t/c ratio
t/c_tip	2	4	%	Wing tip t/c ratio
SHref	400	700	ft^2	Horizontal Tail area
SVref	350	550	ft^2	Vertical Tail area

* Variables Nondimensionalized by wing semi-span

Example configurations

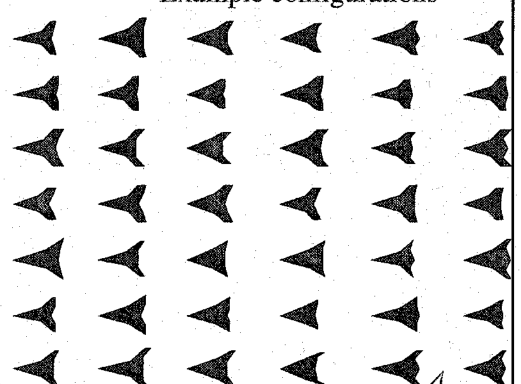


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Figure 25

MODELING AND SIMULATION: VEHICLE MODELING

Once the definition of your design space is established, you need an environment that will model the vehicle and allow you to see how the customer requirements are influenced by the design space. Typically, one uses a sizing and synthesis tool. Yet, standard tools must be enhanced for non-conventional configurations like an HSCT. This is due to the fact that most tools are based on historical data and must be enhanced with higher fidelity analysis tools to give reasonable results. In this example, the aerodynamics internal to the sizing tool were replaced with higher fidelity aerodynamic metamodels which would capture the entire design space under consideration.

This then creates an HSCT specific, physics-based modeling and simulation tool and you are ready to investigate your design space.

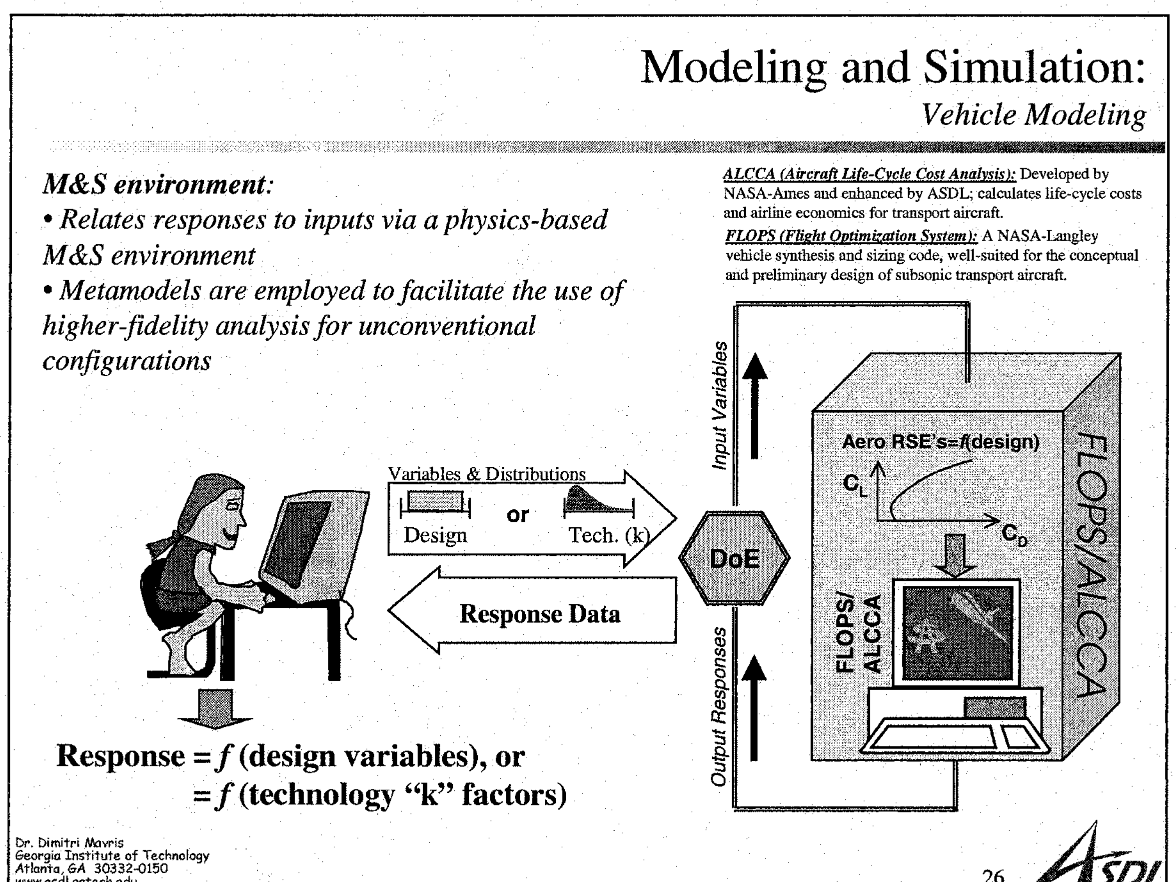

Figure 26

INVESTIGATE DESIGN SPACE: SYSTEM METRIC SENSITIVITIES VIA PREDICTION PROFILES

The RSEs can be visualized within the JMP statistical package with the prediction profile feature shown here. As a side note, system metrics are synonymous with customer requirements.

I want to point out the key info here in the prediction profile. First of all, the metrics are listed on the left and the design variables on the bottom in a non-dimensional form where -1 is the minimum and +1 is the maximum. The redline, or hairline, corresponds to the current value of the design variable settings. And the metric values that result from the current design variables is shown in green. As you move the hairline or change the design variable value, the metrics automatically update.

You can see the influence of each variable on the metrics by the magnitude and direction of the slope. For example, looking at thickness to chord at the tip we can see that as we increase the thickness, the TOGW also increases.

You can also optimize your design variable settings with the desirability feature. You can place the constraint values or the direction that you want a metric and then determine the optimal settings of the design variables. I have shown here the design variable non-dimensional values that correspond to a maximum desirability.

You can also immediately identify the upper and lower bounds of the design space, but you are not sure how close the space is to either value. Is most of the space near the lower bound or the upper bound? To do so, one simply extract the RSEs that are behind the prediction profile and execute a Monte Carlo simulation on those equation with the design variables allowed to vary anywhere within the defined ranges.

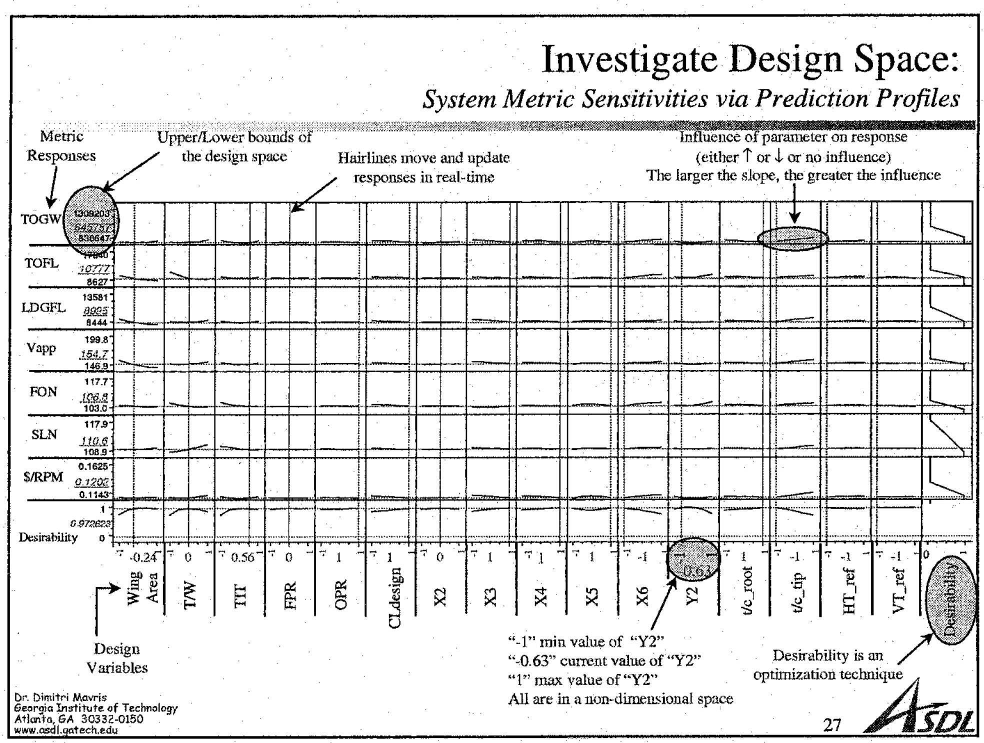

Figure 27

HSCT FEASIBILITY ASSESSMENT: DESIGN SPACE REPRESENTATION

A result of examining the design space is a cumulative distribution representation of you metrics as a function of design variables. Let me explain the information that you get from doing this.

First, you can see the bounds of the design space and how much and or how close the space is to your metric constraints.

Second, you can readily identify the technical feasibility of the design space by looking to see how much of the space is on the feasible side of the constraint target and then read off the Probability value. For example, 4.6% of the space can satisfy the TOFL requirement.

Third, if you look at the metric value at 0 probability, that value is the best that you can EVER achieve with the design space you've defined.

And finally, and most important, you can see which constraints are killing you and are the "show-stoppers" for the program. In this case, none of the space can satisfy the sideline noise AND the space is very far away from the target. Hence, some significant improvements are going to be needed to obtain a feasible solution.

So, what can you do?

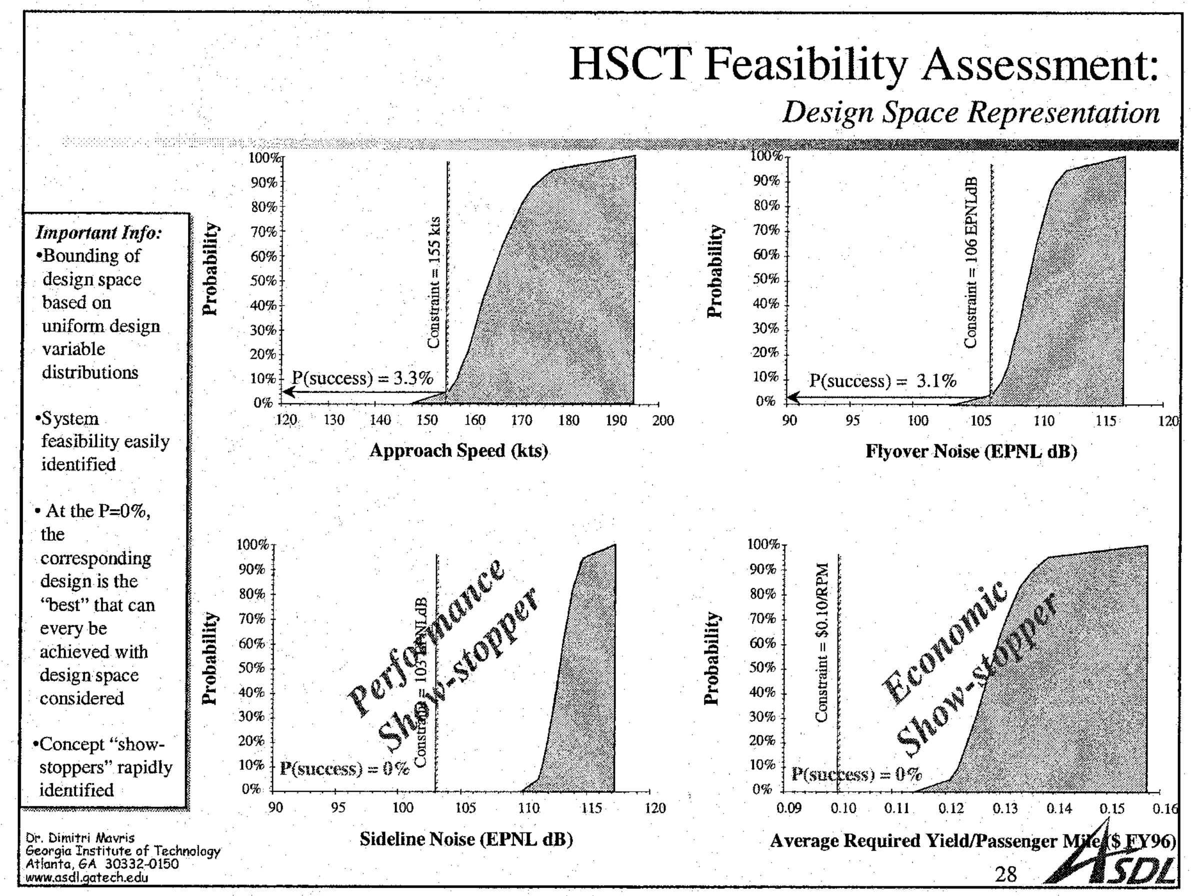

Figure 28

TECHNOLOGY IDENTIFICATION

Based on the fact that technologies are needed to improve the system feasibility, 11 applicable technologies and their associated TRLs were identified either through a literature search or provided from various entities. As you can see, most of the technologies considered are at a TRL of 3. And if you recall from the previous slide, that implies that there is a lot of uncertainty and the anticipated impact has a low chance of being achieved

Technology Identification

- 11 technologies were established from the needed improvements identified in the system feasibility investigation, in addition to enabling technologies
- Associated Technology Readiness Levels (TRLs) were established from a comparison of the current research activities to the TRL descriptions
- Technology Compatibility rules were determined from brainstorming sessions

(Name) Technology	TRL	Purpose
(T1) Composite Wing	3	Wing weight reduction
(T2) Composite Fuselage	3	Fuselage weight reduction
(T3) Circulation Control	4	Increased low speed performance
(T4) Hybrid Laminar Flow Control	3	Cruise drag reduction
(T5) Environmental Engines	3	Reduce noise, fuel burn, and emissions
(T6) Advanced Flight Deck Systems	4	Synthetic vision removes fuselage nose droop weight penalty
(T7) Advanced Propulsion Materials	3	High temp. materials, reduced engine weight, lower fuel burn
(T8) Integrally Stiffened Aluminum Wing Structure	4	Wing weight and part complexity reduction
(T9) Smart Wing Structures	3	Reduced flutter and wing weight
(T10) Active Flow Control	3	Cruise drag reduction
(T11) Acoustic Control	3	Noise suppression

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Figure 29

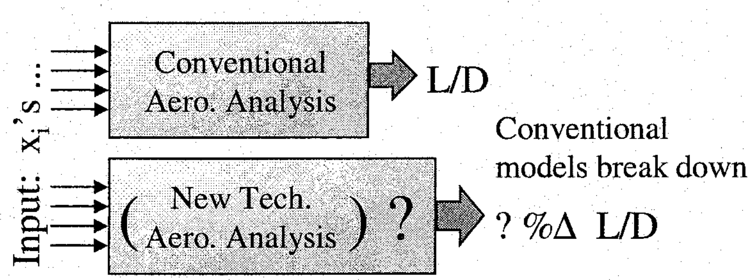
TECHNOLOGY IDENTIFICATION: TECHNOLOGY PRESENTATION THROUGH MAPPING TO "K" FACTORS

Unfortunately, advanced technologies are difficult to assess in an integrated design environment. As mentioned earlier, synthesis/sizing tools are typically based on regressed historical data, which limits or removes the applicability to revolutionary concepts or technologies. However, the impact of generic technologies can be quantitatively assessed with technology impact factors, denoted as "k" factors herein, in the early phases of design. These "k" factors modify disciplinary technical metrics, such as specific fuel consumption or cruise drag that result from a sizing tool. The modification is essentially an incremental change in the technical metric, either enhancement or degradation. In effect, the "k" factors simulate the discontinuity in benefits and/or penalties associated with new technologies. This assessment is performed in the Technology Impact Forecasting environment.

Technology Identification:

Technology Representation through Mapping to "k" Factors

- Formulation in terms of elementary variables does not lend itself to disciplinary or multidisciplinary technology assessment



- The assessment of new technologies must be addressed through the disciplinary metrics (or technology "k" factors) since a mathematical formulation is not yet available

$$\textit{constraints/objectives} = f(k\_L/D_{sub}, k\_L/D_{sup}, k\_\ C_{Lmax}, k\_T1, k\_SFC_{sub}, \ldots)$$

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Figure 30

TECHNOLOGY IDENTIFICATION: TECHNOLOGY IMPACT MATRIX (TIM)

Once the compatibility matrix is established, the potential system and sub-system level impacts of each technology need to be determined. The impacts must include benefits and degradations for an objective assessment.

Based on the probabilistic nature and issues regarding technological developments described above, a Technology Impact Matrix (TIM) is formed for the technologies identified in the Morphological Matrix. Recall that the impact in a synthesis/sizing tool is simulated via changes in disciplinary technical metrics, "k" factors. Consequently, the impact of a technology can be defined by a technical "k" factor vector whose elements consist of the benefits and penalties associated with a specific technology. Each element of the vector has an estimated impact value and an associated distribution based on the technology's TRL. It should be noted that the impact value in the TIM is the "theoretical limit". With this impact value, the technological uncertainty, or distribution associated with a given "k" factor, is defined as a function of TRL and impact value. Not all technologies will affect each element of the vector, but the vector must capture all technologies.

Technology Identification :

TIM: Technology Impact Matrix

- The technical metric impact shown assumes that the impact values are achieved when the technology is fully matured, i.e. TRL=9
- This assumes that the technology can meet the anticipated benefit on schedule and within budget.
- Impact values determined through literature review and supplied by NASA Langley

	Composite Wing	Composite Fuselage	Circulation Control	HLFC	Environmental Engines	Flight Deck Systems	Propulsion Materials	Integrally, Stiffened Aluminum Airframe Structures (wing)	Smart Wing Structures (Active Aeroelastic Control)	Active Flow Control	Acoustic Control	Technology space limits	
Technology "k" factor Vector	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	Min	Max
Wing Weight	-20%			+5%				-10%	-5%	+2%		-35%	+7%
Fuselage Weight		-25%				-15%						-40%	0%
Engine Weight				+1%	+40%		-10%				+5%	-10%	+46%
Electrical Weight			+5%	+1%		+2%	+5%		+5%	+2%	+2%	0%	+22%
Avionics Weight				+5%		+2%	+5%		+2%	+5%	+2%	0%	+21%
Surface Controls Weight			-5%						+5%	+5%		-5%	+10%
Hydraulics Weight			-5%						+5%			-5%	+5%
Noise Suppression					-10%		-1%				-10%	-21%	0%
Subsonic Drag	-2%	-2%		-10%						-5%		-19%	0%
Supersonic Drag	-2%	-2%		-15%						-5%		-24%	0%
Subsonic Fuel Flow			+1%	+1%	-2%		-4%				+1%	-6%	+3%
Supersonic Fuel Flow				+1%	-2%		-4%					-6%	+1%
Maximum Lift Coefficient			+15%									0%	+15%
O&S	+2%	+2%	+2%	+2%	+2%		+2%	-2%	+2%	+2%	+1%	-2%	+17%
RDT&E	+4%	+4%	+2%	+2%	+4%	+2%	+4%		+5%	+5%	+5%	0%	+39%
Production costs	+8%	+8%	+3%	+5%	+2%	+1%	+3%	-3%	-3%	-3%	-3%	-12%	+30%

The sum of reductions and increases defined the limits for the technology space to create metamodels of the metrics as a function of "k" factors within the M&S Environment

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Figure 31

TECHNOLOGY EVALUATION

Next, the technologies identified are applied to the vehicle concept and evaluated. The evaluation provides data and information to the decision-maker whereby selection of the proper mix of technologies may be performed. Yet, the search for the mix that will satisfy the customer requirements is dominated by the "curse of dimensionality". Depending on the number of technologies (n) considered, the combinatorial problem can be enormous. If all technologies were physically compatible, then 2^n combinations would exist considering an "on" or "off" condition. In addition, the technology "k" factor vector that influences a vehicle is probabilistic and a CDF must be generated for each combination, further complicating the evaluation due to the "Curse of Uncertainty". For example, to estimate the impact of uncertainty of a technology combination, a Monte Carlo Simulation of 10,000 random cases are needed. Hence, 10,000*(2n) combinations would need to be evaluated. If the computational expense of the analysis is acceptable, a full-factorial probabilistic investigation could ensue. Yet, if the computational expense is too high, an alternate evaluation method is needed. A potential method for technology down select is a genetic algorithm formulation so as to obtain a more manageable set of alternatives for further investigation.

Technology Evaluation

- The identification of the proper mix of technologies for a given system is dominated by the curse of dimensionality
- *Curse of Dimensionality*: the search space for the mix of technologies which will "best" satisfy the system level metrics or attributes can be enormous, even assuming only an "on"-"off" condition
  - 2^n combinations, where "n" is the number of technologies
    - 11 technologies implies 2048 combinations
    - *20 technologies implies 1,048,576 combinations*
  - Computational expense of the analysis is the primary driver
    - *manageable*: full factorial investigation with metamodel representations
    - *unmanageable*: genetic algorithms or alternative search algorithms
- *Curse of Uncertainty*: Uncertain nature of technologies further complicates the evaluation since a probabilistic analysis is needed to evaluate each of the 2^n combinations

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Figure 32

Technology Evaluation:

"K" Factor Mapping

- If the technologies considered can be represented with "k" factors, a metamodel representation of the system metrics can be used.
- For each row in the TIM, the benefits are summed and the penalties are summed to bound a given "k" factor such that the ranges are defined for the use of a metamodel representation. The ranges define the technology space limits.

Technical Metric "K" Factor Elements	Sum of reductions	Sum of increases
K Factor 1	0	+10
K Factor 2	-40	0
K Factor 3	-20	+25

Range of "k" factor established from TIM

Response = $f(k_1, k_2, \ldots, k_n)$ as obtained from an application of RSM to acquire a second order equation of the form:

$$R = b_o + \sum_{i=1}^{k} b_i k_i + \sum_{i=1}^{k} b_{ii} k_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} k_i k_j$$

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Figure 33

TIF ENVIRONMENT*: VISUALIZATION OF THE TECHNOLOGY MAPPING

Visualization of the influence of the impact factors is performed in the prediction profile feature of the JMP statistical package. The information obtained here is similar to that of the design space investigation.

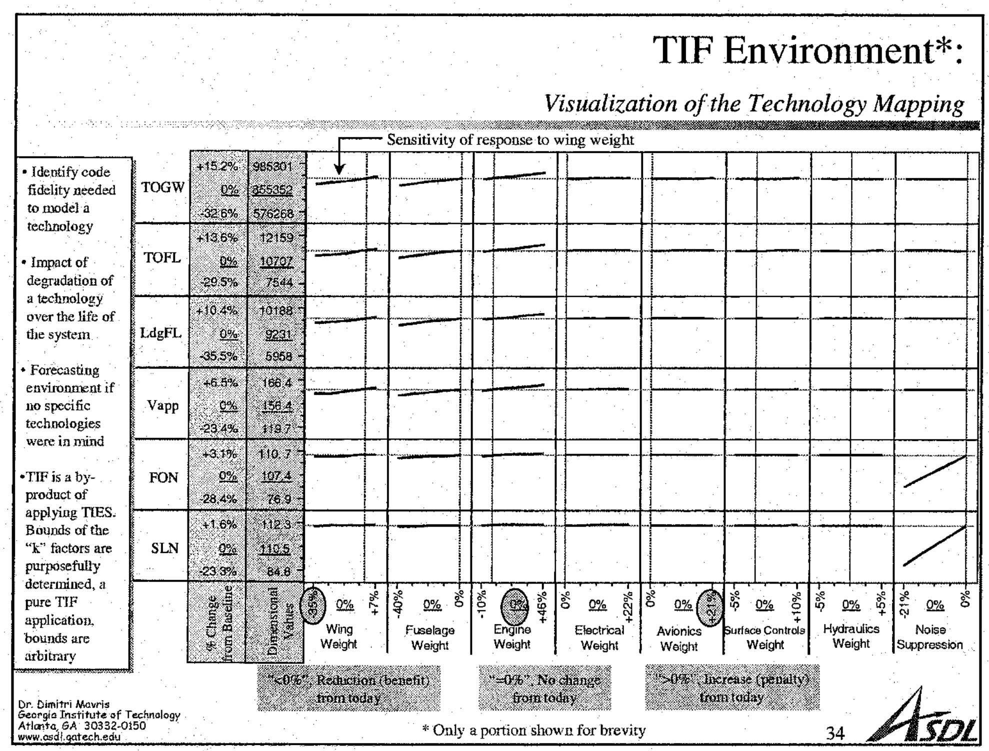

Figure 34

Technology Evaluation

- Deterministic evaluation:
  - For a given technology combination, the vector elements that describe the technologies are summed and inserted into the metric metamodels and the equation evaluated
  - The result is a "theoretical" value of the metric due to the impact of the technology combination
  - Advantage: quick assessment and initial insight to technology impacts
- Probabilistic evaluation:
  - Define each technology vector element as a function of TRL which will result in a distribution for each "k" factor
  - The metric metamodel is evaluated as in the deterministic case except that it is repeated numerous times for a given combination to simulate the uncertainty
  - The result is in the form of a CDF for each metric
  - Advantage: realistic assessment of the impact of technological uncertainty
- Assumption: the impact of the technologies are additive

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Figure 35

Technology Evaluation:

Full Factorial Investigation at "Theoretical" Impact

Case	T1	T2	T3	....	T_n	$Metric_1$	$Metric_2$	....	$Metric_i$
1	-1	-1	-1	....	-1	#	#	....	#
2	-1	1	-1	....	1	#	#	....	#
3	-1	-1	-1	....	1	#	#	....	#
⋮	⋮	⋮	⋮		⋮	⋮	⋮		⋮
2^n	1	1	1	....	1	#	#	....	#

Evaluations of Metric RSEs if all technologies are compatible

"1" implies technology applied
"-1" implies no technology

Metric value is determined with the RSEs based on the technology impact vectors from the TIM

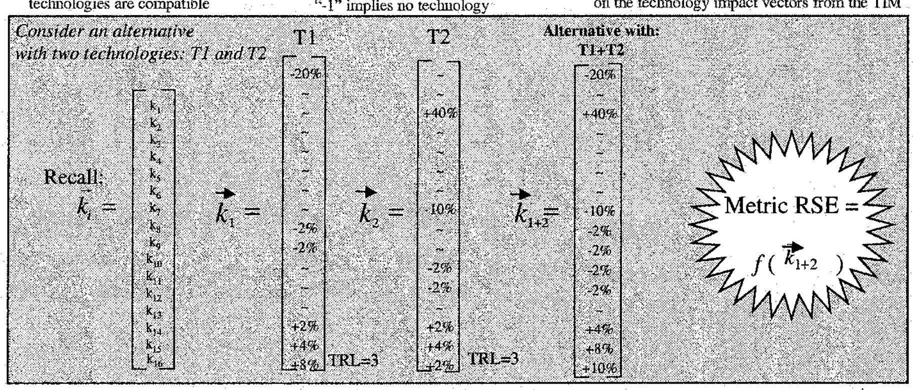

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Figure 36

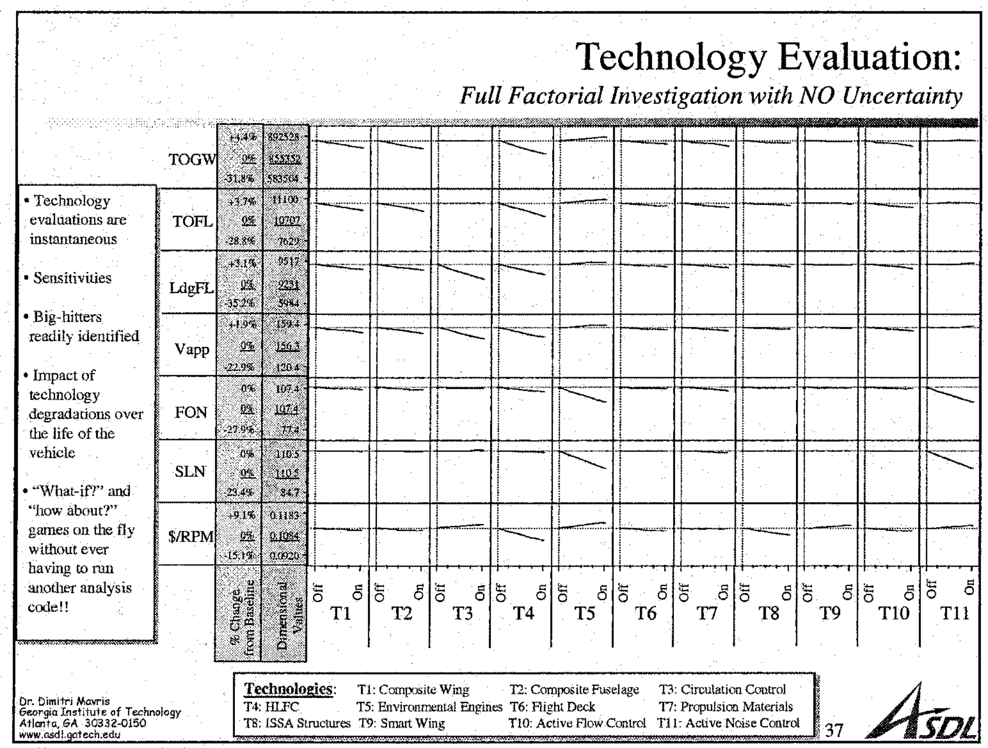


Figure 37

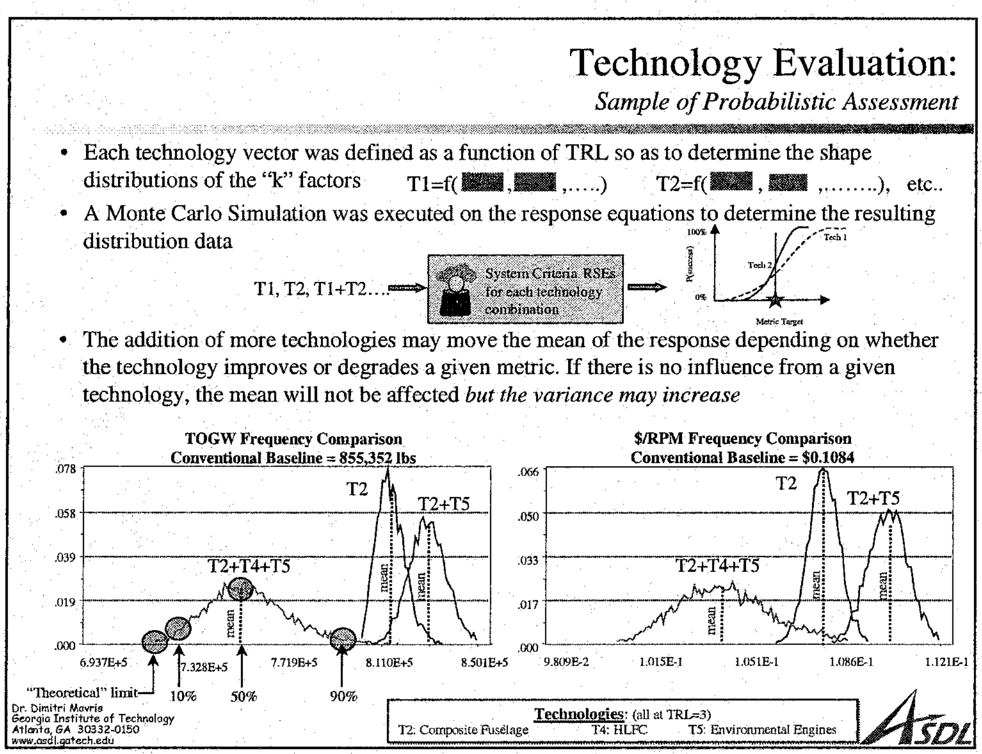
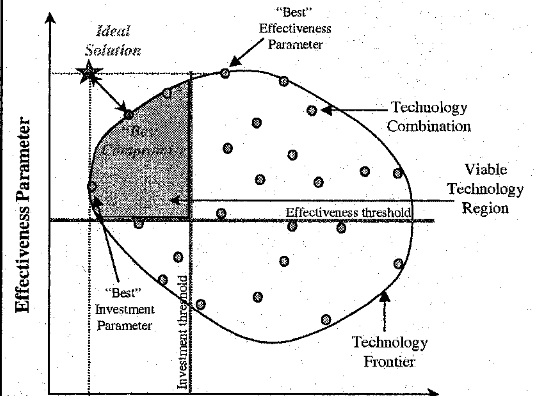


Figure 38

Technology Selection:
Option 2: Technology Frontiers

Due to the multi-attribute and probabilistic nature, visualizing information or results from a MADM approach is not very intuitive. ***Technology Frontiers*** can solve this problem.

Technology Frontier: the limiting threshold effectiveness parameter attainable from any combination of technologies for different confidence levels.



- Two primary *effectiveness parameters*, such as **Performance** and **Economics**, can be utilized to compare various technology alternatives and may be constructed from a *user defined utility function for which maximization is desired.*
- Subjectivity introduced through weightings.
- Threshold limits may be placed on the effectiveness and the investment cost and the combinations that satisfy the thresholds can be readily identified.

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* *Ideal comparison metric*

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Figure 39

Technology Selection:
Option 2: Performance Effectiveness with NO Uncertainty

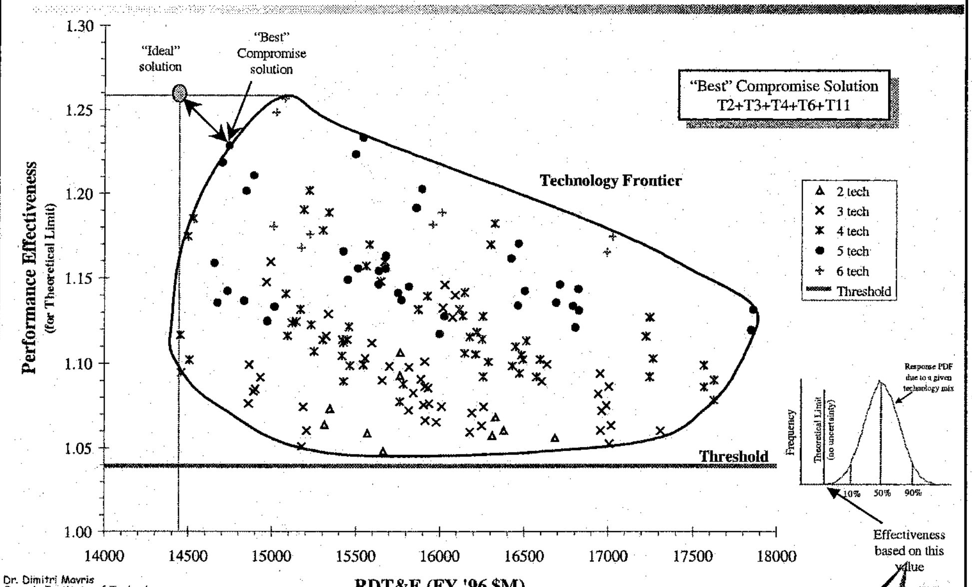

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Figure 40

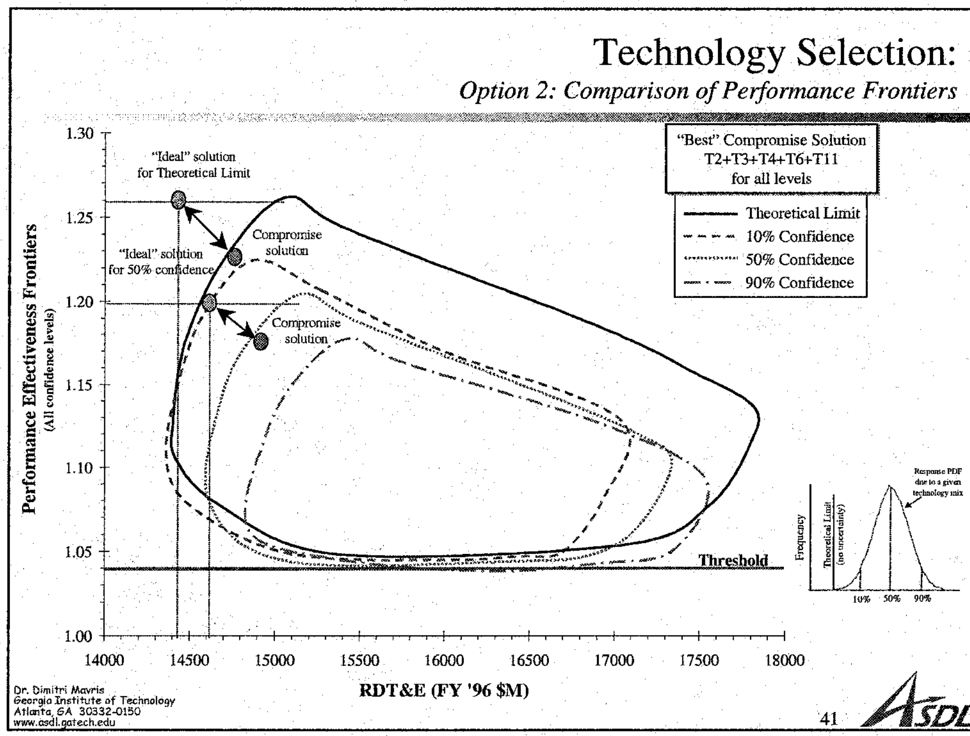


Figure 41

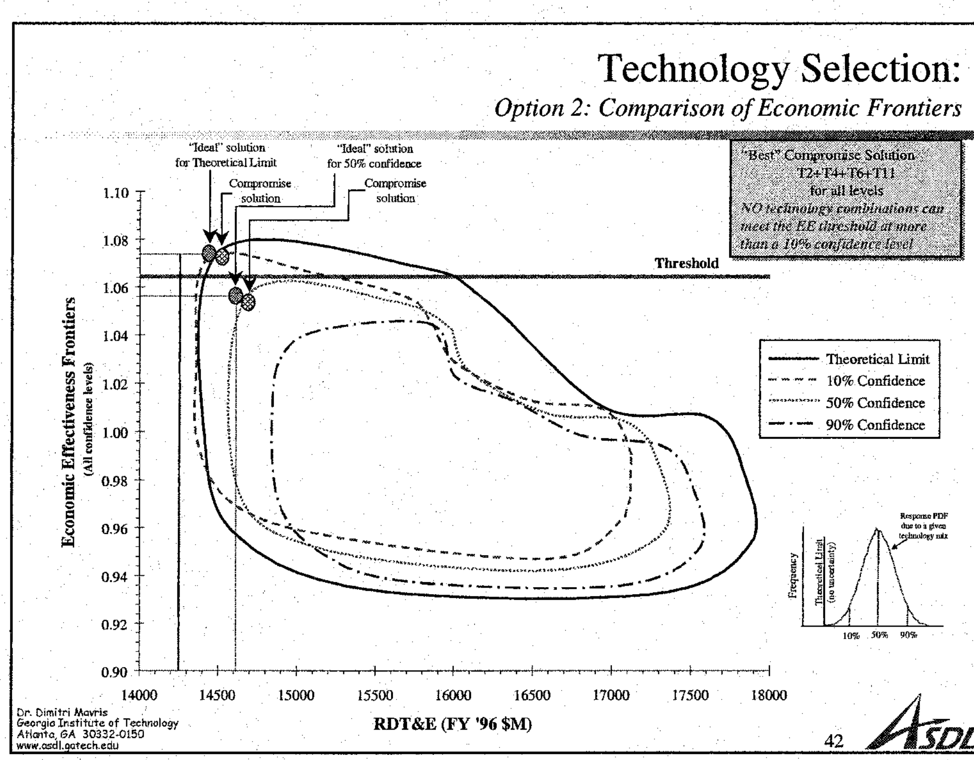
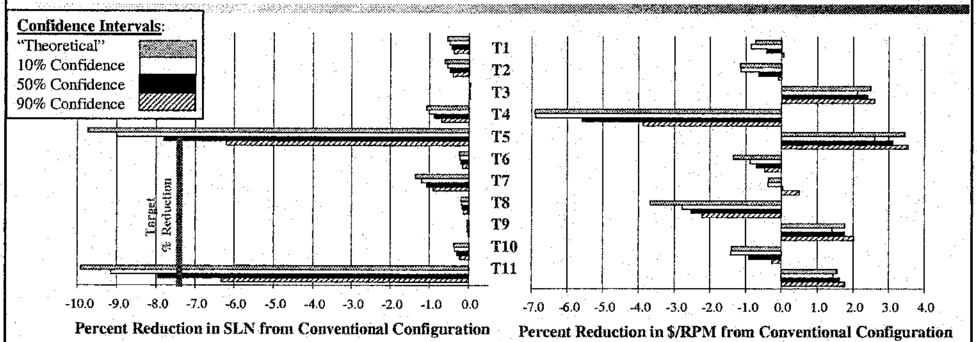


Figure 42

Technology Selection:

Option 3: Resource Allocation



Technologies: T1: Composite Wing; T2: Composite Fuselage; T3: Circulation Control; T4: HLFC; T5: Environmental Engines; T6: Flight Deck; T7: Propulsion Materials; T8: ISSA Structures; T9: Smart Wing; T10: Active Flow Control; T11: Active Noise Control

- Decision-maker may readily identify a technology's influence on a given system metric and compare the performance influence and the economic influence.
- Compare confidence level to target reduction needed for feasibility
- Identify the contribution of individual technologies to optimally direct resources
- T5 provides sufficient SLN reduction, but extreme degradation to $/RPM

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Figure 43

Conclusions

- A comprehensive, robust, and structured process for the systematic down-select of technologies for the problem at hand.
- Process provides valuable insight to the decision-maker in the conceptual phases of design to optimally direct program resources.
- No one technology combination can be considered the universal solution since the selection process is riddled with subjectivity. *TIES* allows for a quantification and tracking of the subjectivity.
- Future work will focus on:
  - Incorporating schedule and budget issues regarding the development of technologies and quantifying the impact on a system
  - Create a recipe for *TIES* based on generic problem that may be encountered during a design process

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Figure 44

Nondeterministic Approaches Potential for Future Aircraft Support

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USAGE OF NONDETERMINISTIC MODELS

In the current aerospace environment, which poses continuing challenges to "do more with less" the adverse effects of uncertainty on decision making must be recognized and minimized. Nondeterministic approaches are predictive tools that permit uncertainties to be quantified, by a variety of models, providing decision makers a sound technical basis for trade-offs among performance, schedule and cost. The illustrative examples show a broad scope for potential applications that don't require specialized software or advanced statistical skills.

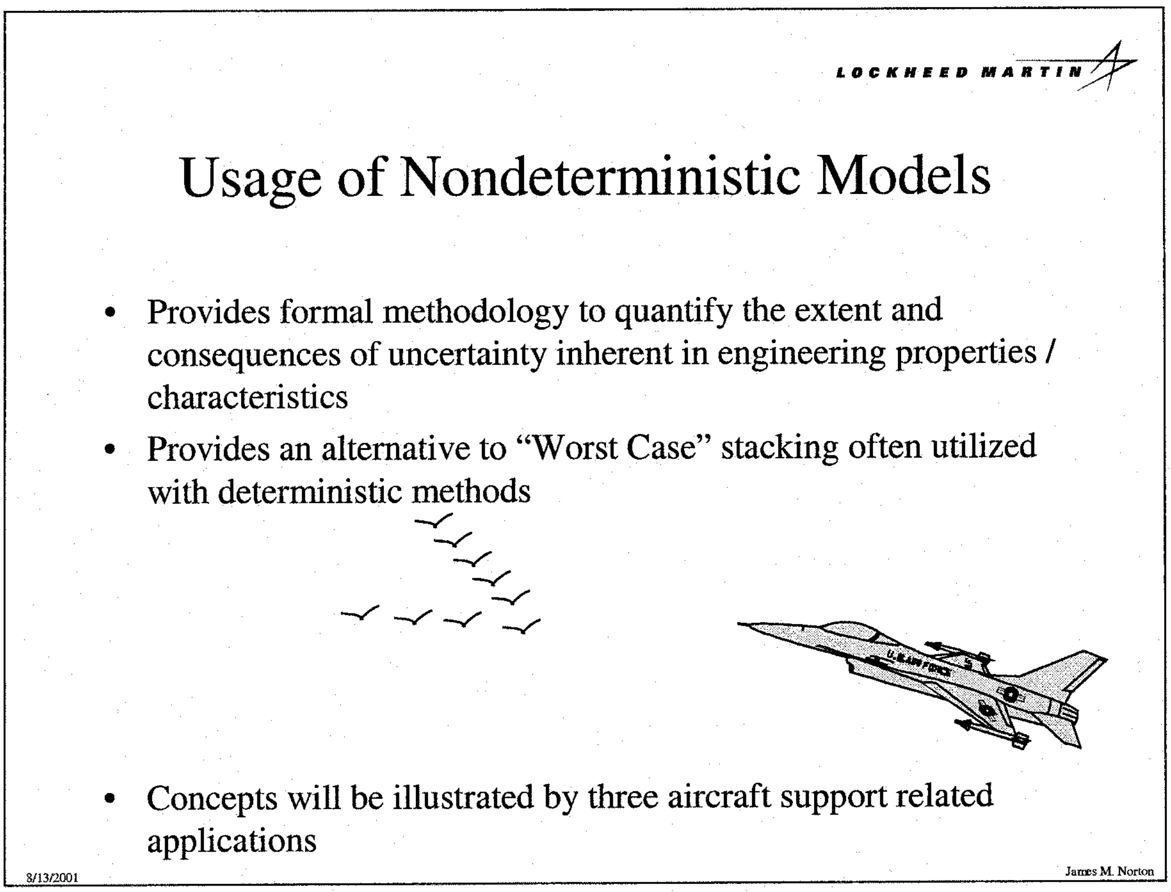

Figure 1

ASSESSING THE EFFECTIVENESS OF TIME CHANGE INTERVALS

One method of avoiding equipment failures is to remove the equipment from service at fixed flight hour intervals. Although failures are avoided, some remaining equipment life is lost and the total number of maintenance actions is increased. Analysis of various conditional life distributions can help decision makers determine the appropriate policy.

LOCKHEED MARTIN

Assessing the Effectiveness of Time Change Intervals

- Equipment whose life exhibits wear-out characteristics can be removed from service at fixed flight hour intervals resulting in:
  - Reduced failures
  - Increased maintenance actions
  - Loss of potential remaining equipment life

- Analysis of the Nondeterministic equipment life distribution can help decision makers determine the appropriate policy.

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Figure 2

ASSESSING THE EFFECTIVENESS OF TIME CHANGE INTERVALS

Suppose a generator has a Weibull life distribution with mean = 800 flight hours and a shape parameter = 1.1. A sketch of the life and conditional life distributions may provide some preliminary insight as to the effectiveness of a time change after X hours of service. The risk of failure prior to the time change, as well as the average remaining life lost, is easily computed as shown from common spreadsheet functions.

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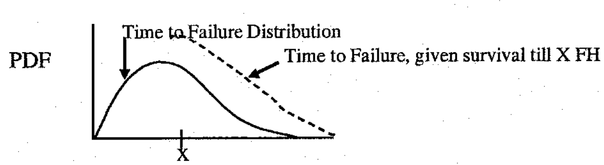
Assessing the Effectiveness of Time Change Intervals

An example –

Suppose a generator has a Weibull life distribution with mean = 800 flight hours. A literature source suggests a Weibull shape parameter = 1.1. We wish to evaluate the effectiveness of removing and replacing the generator every X flight hours.



Probability failure prior to X = $1 - \text{EXP}\left(-\left(\frac{x}{\text{scale}}\right)^{\text{shape}}\right)$

Average remaining life =

Scale • EXP (K1 + GAMMALN (K2)) • (1 – GAMMADIST (K1, K2, 1, TRUE)) – X

Where $K1 = \left(\frac{x}{\text{scale}}\right)^{\text{shape}}$, K2 = 1 + 1/shape,

GAMMALN ( ) = Excel Supplied Function

GAMMADIST ( ) = Excel Supplied Function

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Figure 3

The results in the table show modest reductions in failures from time changes (shape =1.1), which need to be assessed in conjunction with the consequences of failure. The likely results and sensitivity of results to variations in model parameters can be examined before any data is available. Statistical estimation methods are used to draw inferences about model parameters from data.

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Assessing the Effectiveness of Time Change Intervals

WEIBULL SHAPE

Time Change Interval	**1.1**	**1.3**	**1.5**	
400	20	20	20	# Time Changes
	8.8	7.0	5.7	# Failures (Weibull Renewal)
	14851	13179	12032	Unused Life
800	10	10	10	# Time Changes
	9.3	8.2	7.4	# Failures (Weibull Renewal)
	7160	5918	5044	Unused Life
No Time Change	0	0	0	# Time Changes
	10	10	10	# Failures (Weibull Renewal)
	0	0	0	Unused Life

TABLE ENTRIES ARE AVERAGES FOR 8000 FH A/C LIFE.

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Figure 4

A SUFFICIENTLY LARGE PROBABILITY OF A BRAKE FIRE

Frequently during landing / taxi military aircraft experience significant increases in brake temperature which, if coupled with hardware failures in the fuel system, could result in a fire during refueling. A nondeterministic model can estimate the frequency of fires, to help determine what (if any) interventions are needed.

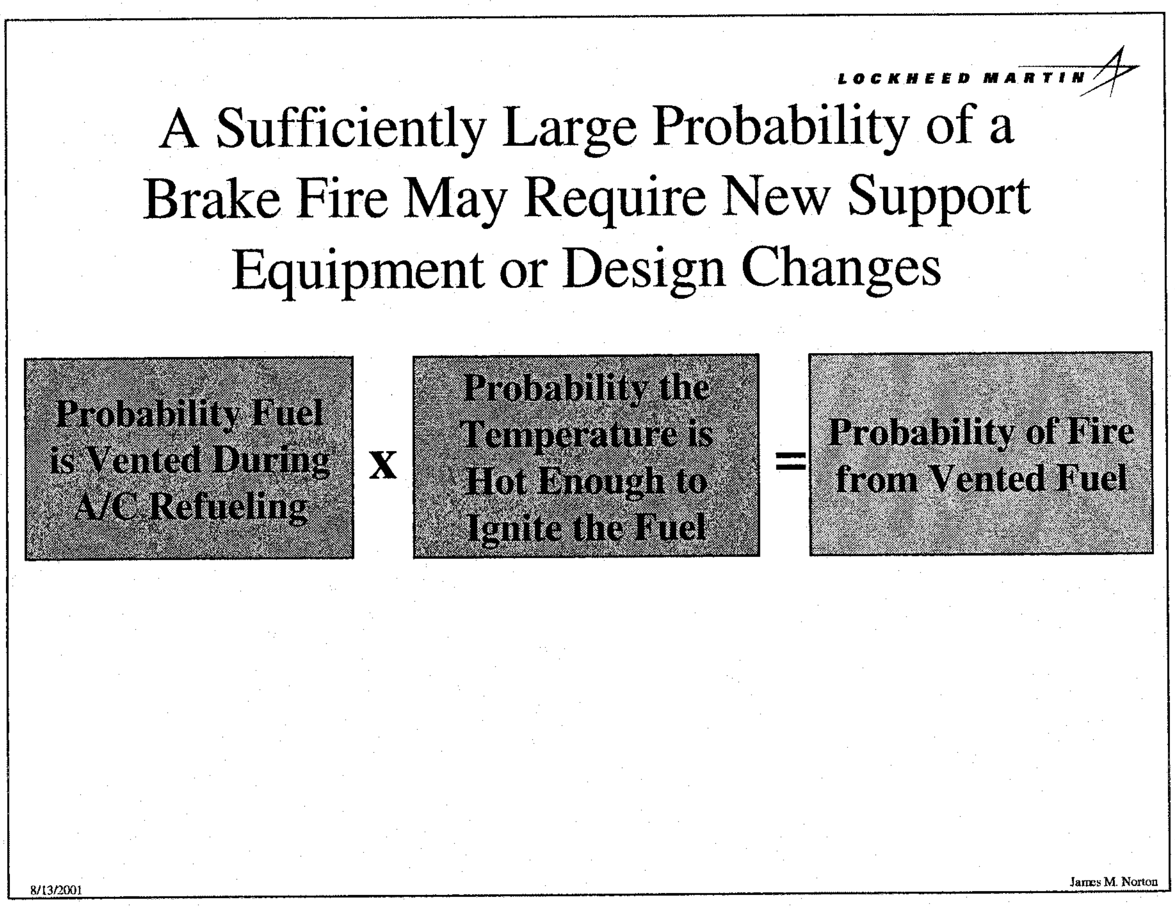

Figure 5

CONDITIONAL PROBABILITY BRAKE TEMP

Key factors that determine brake temperature are defined during discussions with technical experts. Each factor is characterized by a probability distribution, derived from data and/or inputs from experts. The individual distributions are combined, reflecting any significant correlations, to form the brake temperature distribution. Live testing under realistic environmental conditions results in an estimated fuel ignition distribution that is combined with the brake temperature to quantify risk.

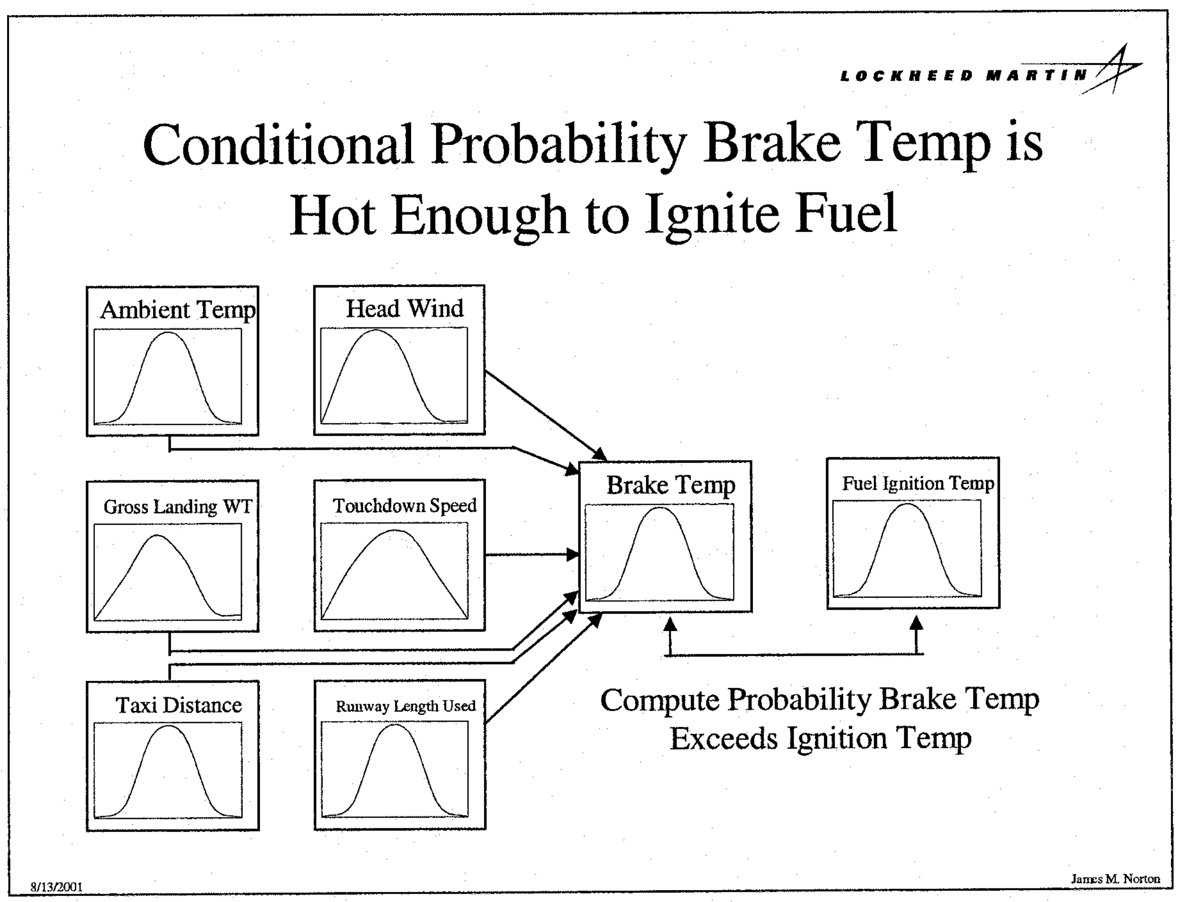

Figure 6

PRICING REPAIRS FOR A FIXED TIME PERIOD

To help customers plan for the costs associated with repair of equipment failures in their aircraft fleet, a contractor may offer to provide repairs for a fixed time period at a pre-specified price. One NDA approach to help establish an equable price is to model cost as a compound random variable.

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Pricing Repairs for a Fixed Time Period

- All Equipment Failures that Occur During a Fixed Time Period will be Repaired for a Pre-Specified Price
- One NDA Approach to Help Establish an Equable Price is to Model Cost as a Compound Random Variable:

Total Cost = $C_1 + C_2 + \text{----} + C_n$

where

Ci = Random Variable Cost of i^{th} Repair

N = Random Variable Representing Number of Repairs in the Defined Time Period

8/13/2001

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Figure 7

PRICING REPAIRS FOR A FIXED TIME PERIOD

Frequently, the number of failures to be repaired in a fixed time period can be characterized by a Poisson distribution. Repair cost means and variances are then utilized to compute the mean and variance of total repair cost. The risk that the cost of the repairs will exceed the price charged can be assessed after a distributional form for cost is selected.

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Pricing Repairs for a Fixed Time Period

- The Mean and Variance of Total Cost are:

$$\text{Mean}\begin{bmatrix}\text{Total}\\ \text{Cost}\end{bmatrix} = \text{Mean}\,[\,N\,] \bullet \text{Mean}\,[\,C\,]$$

$$\text{Variance}\begin{bmatrix}\text{Total}\\ \text{Cost}\end{bmatrix} = \text{Mean}\,[\,N\,] \bullet \text{Variance}\,[\,C\,] + [\text{Variance}\ N] \bullet [\text{Mean}\ C]^2$$

Where Ci is Independent, Identically Distributed.

- Use Exact or Approximate Distribution to Evaluate Risk

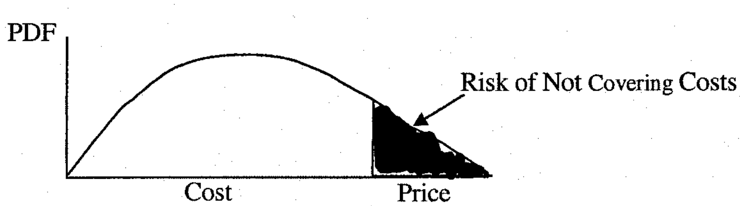

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Figure 8

DIVERSE SUPPORT RELATED APPLICATIONS BENEFIT FROM NONDETERMINISTIC APPROACHES

The use of nondeterministic methods for support-related applications has a long history, with many companies establishing formal specialty groups that concentrate on application areas, such as safety, reliability, maintainability, and logistics support. Basic models in the specialty area are generally well known and have developed some commonly accepted standards for use. The rapidly increasing capability to collect, store, process, and share data will reveal new relationships among variables, leading to the development of more sophisticated nondeterministic methodology.

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Diverse Support Related Applications Benefit from Nondeterministic Approaches

- Tech Order Changes (Often Inspection Related)
- Rates of Damage Accumulation
- Spares Requirements
- Warranty Provisions
- Repair Turnaround Capability
- Diagnostics / Health Monitoring

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Figure 9

KEYS FOR SUCCESSFUL IMPLEMENTATION

As advances in nondeterministic methods are achieved, some basic keys for successful implementation remain unchanged. Although the items listed are fairly obvious and not exhaustive, they are easy to forget.

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Keys for Successful Implementation

- Establish clear objectives / expectations for model results
- Develop model structure with guidance from experts in affected areas
- Collect sufficient reference information / data for credible model parameter estimates
- Summarize / communicate results that are technically rigorous, yet readily understood
  - Avoid technical jargon
  - Delineate assumptions
  - Graphically depict results, where possible

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Figure 10

ANSYS Probabilistic Design System
Exploring Randomness and Scatter Reveals A Simple Truth

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Team Leader Probabilistic Design
ANSYS Inc.
Canonsburg, PA 15317

ANSYS PROBABILISTIC DESIGN SYSTEM

In December 2000 ANSYS Inc. has released the version 5.7 of its ANSYS Finite-Element program. This release (and any following ones) has a probabilistic design system integrated into it. This tool enables users to take uncertainties of their Finite-Element model input parameters into account. The probabilistic approach is more realistic and closer to reality than the purely deterministic approach, which tends to ignore uncertainties. Using the ANSYS Probabilistic Design System (ANSYS/PDS) users can quantify the quality and the reliability of their products and consequently make informed decision on how to improve their products with respect to quality and reliability.

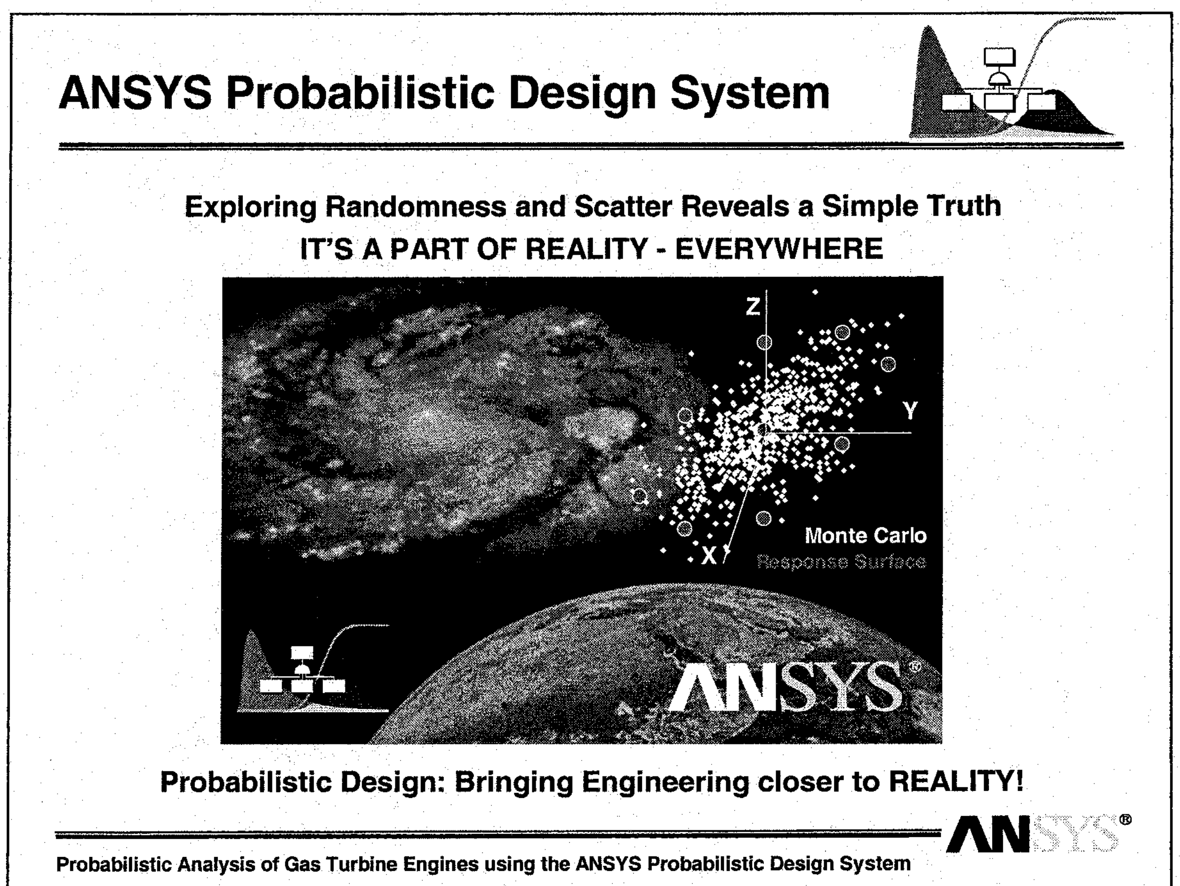


Figure 1

PROBABILISTIC DESIGN SYSTEM: INTRODUCTION

If we analyze a component (for example a turbine blade like those shown here), then we start out with the fact that the component is described by a certain set of input parameters, namely material properties, geometric extensions of the component and boundary conditions that describe how the component is loaded and where and how it is fixed. Then the component is analyzed, and as result we can look at its deformation and review the stresses and strains. In addition, we can assess its fatigue lifetime or its creep behavior and such. Probabilistic Design is based on the fact that all input parameters are subjected to scatter. Take, for example material, properties. If you measure a particular material property then you will observe measurement values that are different from specimen to specimen. Also, the geometric extensions of a component can only be manufactured within certain tolerances. To strive for perfection is physically not possible and even trying to get close to perfection is not reasonable in financial terms. Also loads and boundary conditions are subjected to scatter, i.e. there are some uncertain influences that we have to accept and live with. As a direct consequence we have to face the fact that the output parameters are subjected to scatter as well, i.e. they are uncertain as well. ANSYS has developed a probabilistic design system that can take the randomness of such input parameters into account and provide the necessary conclusions.

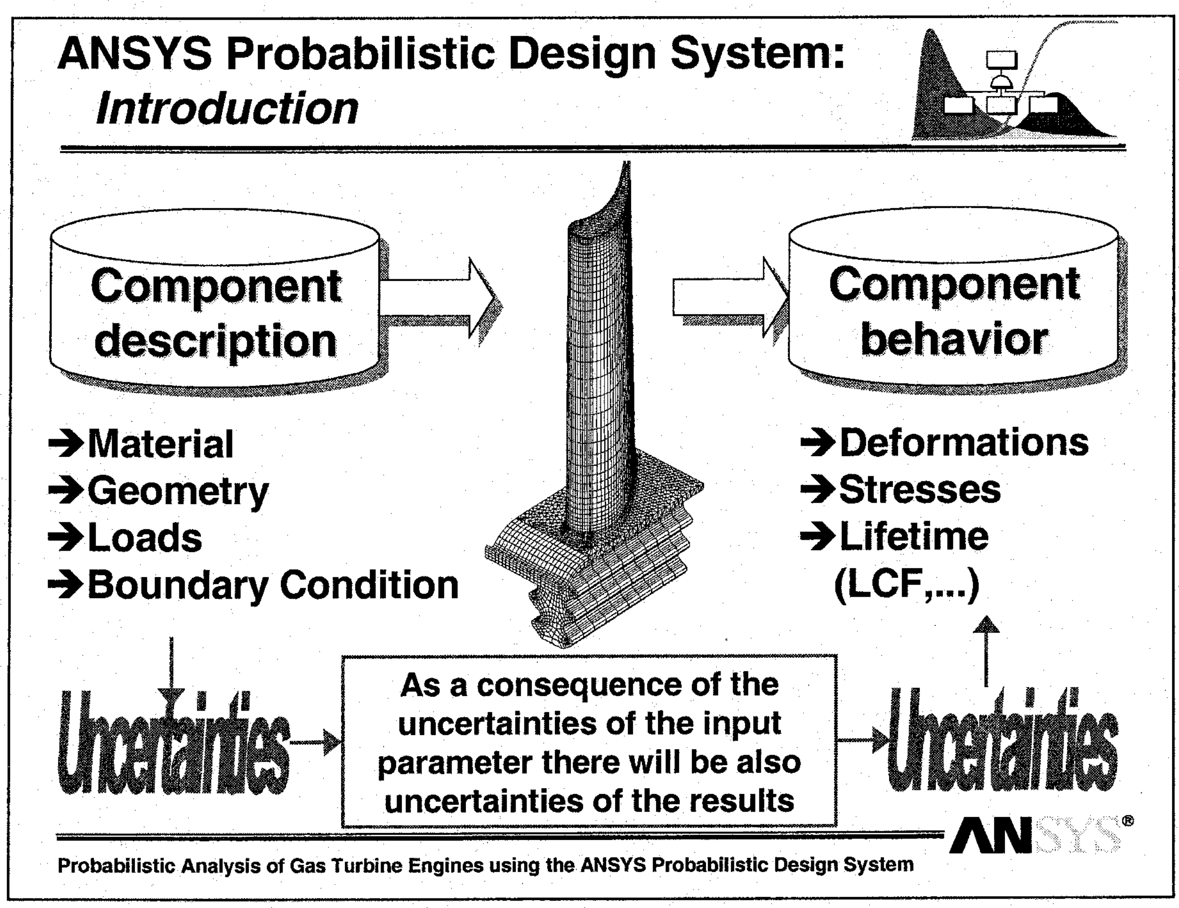


Figure 2

PROBABILISTIC DESIGN SYSTEM: FEATURES

The ANSYS probabilistic design system is available at no charge for customers having an ANSYS license. It is automatically a part of any ANSYS product. It works with any ANSYS model no matter what the underlying physics is. It allows for a large number of random input and output parameters. The random input parameters can be correlated in order to address random fields. Two widely used and very robust probabilistic methods have been implemented, namely then Monte Carlo Simulation method and the Response Surface Method. Both are available with various sampling techniques. In order to fit response surfaces, the ANSYS/PDS offers several sophisticated regression analysis techniques. Included are techniques to apply transformation functions for cases where a quadratic response surface is not sufficient. Also filtering mechanisms can be used that will filter out insignificant terms in the regression model in order to avoid the "over-fitting" problem. To reduce the wall clock time of a probabilistic analysis, the PDS comes with a tool that will automatically distribute the various jobs in a heterogeneous network of computers. This includes the capability to submit a job that has failed due to CPU or network problems to another CPU. Naturally, the ANSYS/PDS offers a great variety of tools to visualize the probabilistic results, such as histogram plots, cumulative distribution plots, scatter plots, sensitivity plots and so on.

ANSYS Probabilistic Design System:
Features

- **The ANSYS/PDS is FREE for every ANSYS customer**
- **It works with *any* ANSYS model (static, dynamic, linear, non-linear, thermal, Structural, Electro-magnetic, CFD ...)**
- **It allows for a large number of random input and output parameters**
- **It has 10 statistical distributions for random input variables**
- **The random input variables can be correlated**
- **Probabilistic methods:**
  - **Monte Carlo - Direct & Latin Hypercube Sampling**
  - **Response Surface - Central Composite & Box-Behnken Designs**
- **Sophisticated regression analysis capabilities for response surface fitting (automatic transformation functions for a "more than quadratic" fit, automatic filtering of insignificant regression terms to avoid "over-fitting" problem)**
- **Use of distributed, parallel computing techniques for drastically reduced wall clock time of the analysis**
- **Comprehensive probabilistic results (convergence plots, histogram, probabilities, scatter plots, sensitivities, ...)**
- **State-of-the art statistical procedures to analyze and visualize probabilistic results**

Probabilistic Analysis of Gas Turbine Engines using the ANSYS Probabilistic Design System

Figure 3

PROBABILISTIC DESIGN SYSTEM: CUSTOMER BASE

As many people know, ANSYS is widely used in the industry, and here you see only a few of our customers who gave us permission to show their company logo. The ANSYS Probabilistic Design System is an integral part of ANSYS 5.7. More than 35 companies are already using it worldwide.

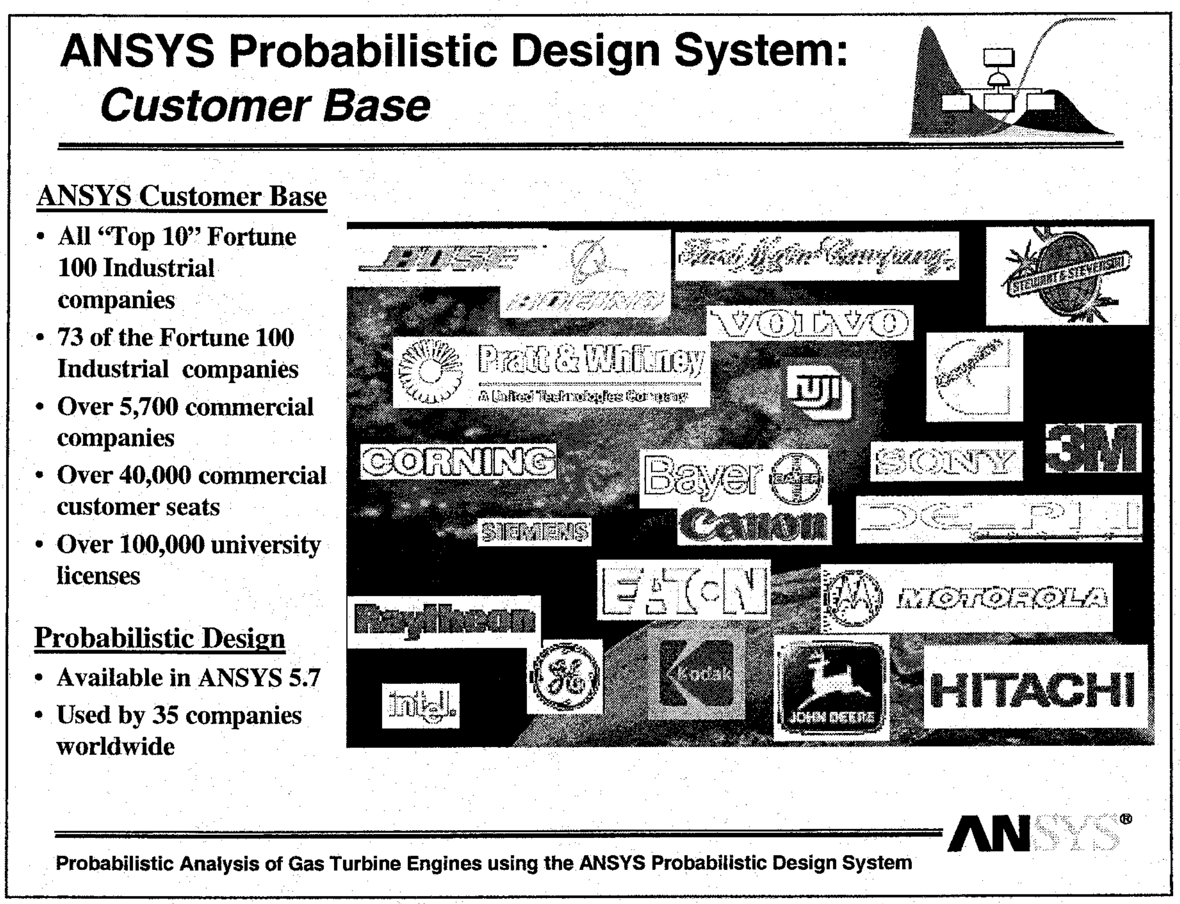


Figure 4

RELIABILITY OF COMPONENTS: EXAMPLE TURBINE BLADE

As an example for the application of the ANSYS probabilistic design system, the probabilistic analysis of a turbine blade is shown here. The example is a cooled (hollow) rotating blade. The probabilistic analysis includes the randomness of a total of 17 input parameters. For example, the blades are manufactured by precision casting. During casting of the blade a slight shift of the core that makes up the hollow cavity can occur. This core shift makes the wall of blade thinner on one side and thicker on the other. Also there is an oxidation protection coating on the hot gas surface of the blade. The thickness of the coating is not an exact value after it is applied, but variations from the targeted thickness may appear. It is not necessary to explain all random input parameters as listed here. Suffice it to say that the random input parameters are from all categories, namely geometry, material and loads. Also it should be emphasized that various different statistical distribution functions can be applied to describe and quantify the randomness of the input parameters, such as the Gaussian distribution, the uniform distribution or the lognormal distribution (the ANSYS/PDS has many more). This Finite-Element model has about 60,000 elements and 180,000 nodes. One single analysis run includes a thermal analysis to evaluate the temperature field (shown here) and a structural analysis to evaluate the thermo-mechanical stresses. Based on these results the low cycle fatigue lifetime (LCF), the creep lifetime and the time until the oxidation protection layer has been eroded through is calculated. One complete analysis as described takes about 2 hours.

Reliability of Gas Turbine Components:
Example Turbine Blade

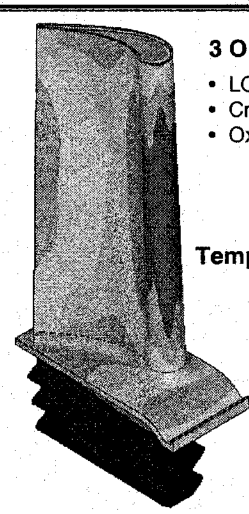
17 Random Variables for input variables

Geometry parameters	
• Cooling channel shift (Circumference)	UNIF(-0. 6,0.6)
• Cooling channel shift (Axial)	UNIF(-0. 6,0.6)
• Thickness of oxidation protection	LOG(0.3,0.03)
Material parameters	
• Young's Modulus (*)	NORM(1.0,0.04)
• Density (*)	NORM(1.0,0.05)
• Therm. Expansion (*)	NORM(1.0,0.05)
• Heat conduction (*)	NORM(1.0,0.05)
• Heat capacity (*)	NORM(1.0,0.04)
• Oxidation depletion rate (*)	LOG(1.0,0.05)
Strength related material parameters	
• LCF curve (*)	LOG(1.0,0.15)
• Creep rupture curve (*)	LOG(1.0,0.10)
Thermal Boundary Conditions	
• Hot gas temperature	NORM(0.0,25.0)
• Hot gas heat transfer coefficient (*)	LOG(1.0,0.2)
• Cooling air temperature	NORM(0.0,10.0)
• Cooling air heat transfer coeff. (*)	LOG(1.0,0.1)
• Hot gas mass flow (*)	NORM(1.0,0.03)
• Cooling air mass flow (*)	NORM(1.0,0.05)

(*) Factor relative to nominal value or curve

3 Output parameters

- LCF lifetime
- Creep lifetime
- Oxidation lifetime



Temperatures

Thermo-mechanical analysis
60'000 Elements (quadratic)
180'000 Nodes
2 h of CPU time per analysis

ANSYS®

Probabilistic Analysis of Gas Turbine Engines using the ANSYS Probabilistic Design System

Figure 5

RELIABILITY OF COMPONENTS: FAILURE PROBABILITY OF TURBINE BLADE

Crucial in today's business environment is the development of reliable products. Only reliable products keep the occurrence of premature failures (a failure that happens before the end of the warranty period) at an acceptable level or avoid such failures completely. The most important measure for a reliable product is a low failure probability. As a result of the probabilistic analysis in this diagram, the probability of a failure due to one of the three failure modes (LCF, creep, oxidation) is plotted versus the operation time in years. A particular failure probability can be derived from this plot by choosing a value on the X-axis for the operation time (i.e. the time how long the blade is supposed to be in service) and then going up to the probability curves related to the failure modes and reading the probability on the Y-Axis. In this diagram, the results calculated with the "response surface method" are compared with the results gained from 500 Monte Carlo simulations. In this example, the Monte Carlo Simulation results provide benchmark values the "response surface method" results should agree with for the failure probability ranging from 2% to 98%. Obviously, there is a very good agreement between the results of the two methods in this probability range.

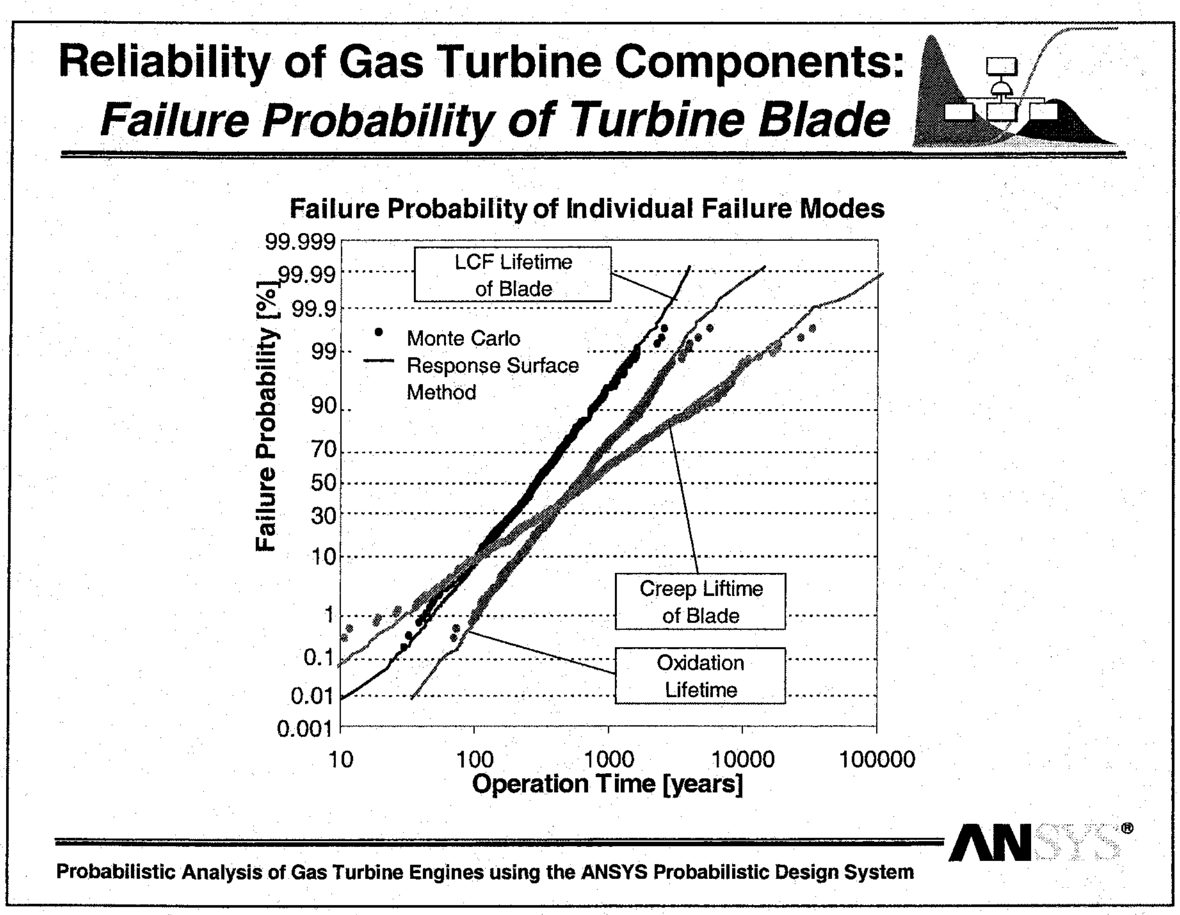


Figure 6

RELIABILITY OF COMPONENTS: SENSITIVITIES FOR TURBINE BLADE

Probabilistic methods also automatically deliver probabilistic sensitivities. These sensitivities describe how much the scatter or the failure probability of a particular random output parameter (shown here is the LCF lifetime) is affected by the scatter of the individual random input variables. The ANSYS/PDS sorts the input variables into two groups - the significant and the insignificant ones. Then the significant input variables are ranked by the importance and plotted. These probabilistic sensitivities provide highly valuable information in many ways. If the resulting failure probability is too high, then we need to improve the design in order to achieve an acceptable level. The sensitivities clearly indicate which input variables are the drivers of the high failure probability. Hence, the input parameters must be tackled in the order of their importance. There is no point in focusing on unimportant parameters. Sometimes the scatter of some input parameters are just estimated based on no or very little measurement data. If these parameters turn out to be very important for the reliability of the design, this indicates that lab tests should be done to collect more data about that input parameter. If the current design is sufficient, i.e. has an acceptably low failure probability, and then there is typically the need to save money without sacrificing the achieved reliability. In this case, the manufacturing requirements for the input parameters can be relaxed and a possibly coarser or cheaper manufacturing process can be chosen, or the quality assurance requirements for those parameters can be relaxed. This typically leads to huge savings in the manufacturing process.

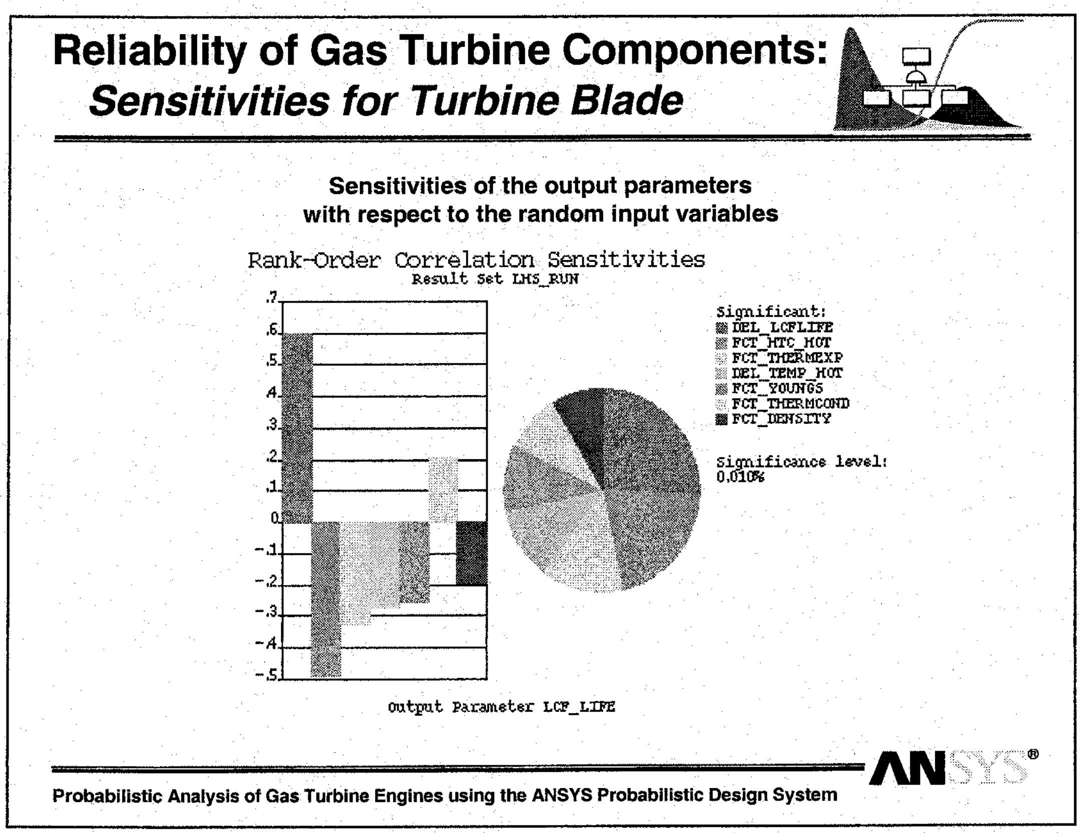


Figure 7

RELIABILITY OF COMPONENTS: EXAMPLE TURBINE STAGE

Products, of course, usually consist of many components and not just one. Therefore, to assess the reliability and quality of a product, it is important to evaluate the system reliability of all parts the product is made of. In the example here, we consider an entire turbine stage consisting of 100 turbine blades on the circumference plus the turbine disk on which these blades are mounted. For the turbine blades the same input parameters are considered as uncertain input variables as described above. For the turbine disk, a separate finite-element model has been built and evaluated for its fracture mechanical lifetime. The fracture mechanical lifetime is driven by the existence of a crack in the disk center that is small enough to just be overlooked by non-destructive inspection. The crack will grow in size due to the cyclic loading of the disk by the start-up and shutdown cycles. To model the crack growth a simple Paris law has been used. The crack growth is governed by the initial crack size, the fracture toughness and the crack growth parameters of the Paris law, all of which are included in the probabilistic analysis as random input parameters.

Reliability of Gas Turbine Systems:
Example Turbine Stage

Turbine Stage

100 Turbine blades on circumference
1 Turbine disk

Random input variables for turbine blades

- Geometry parameters (as described above)
- Material parameters (as described above)
- Strength parameters (as described above)

Random input variables for turbine disk

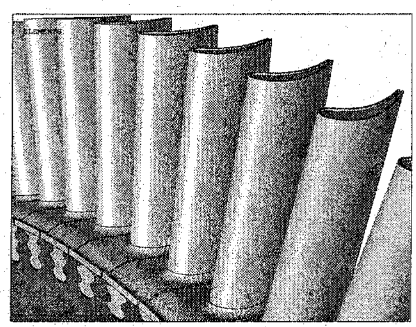
Cyclic crack growth of an existing crack in disk center that is just not detectable in non-destructive inspection

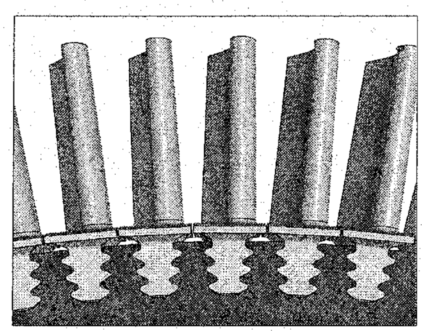
$$\frac{da}{dN} = A\Delta K_I^n = A\left(\Delta\sigma\sqrt{a}Y\right)^n \xrightarrow{Zyklen} K_{I,\max} = K_{Ic}$$

- Initial crack size a_{init}
- Fracture toughness K_{Ic}
- Crack growth parameters A and n

Random input variables for entire stage

- Thermal boundary conditions (as described above)





Probabilistic Analysis of Gas Turbine Engines using the ANSYS Probabilistic Design System ANSYS®

Figure 8

In the top half, the results for the individual blades are shown. This is the same picture as already shown before. Shown in the bottom half is the result for the turbine disk. The Finite-Element model of the disk shows the stress field in the disk. The failure probabilities due to a fracture mechanical failure of the disk is shown in the bottom right diagram.

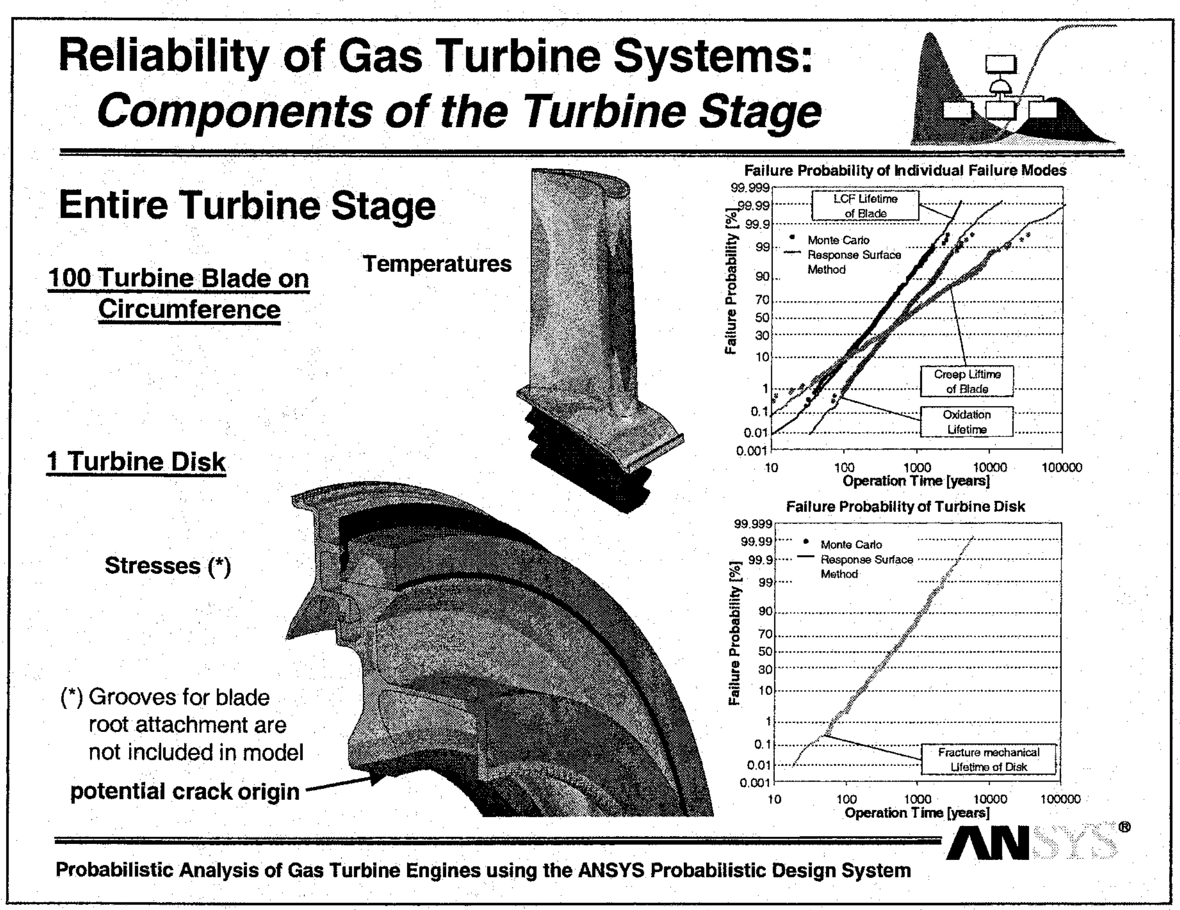


Figure 9

RELIABILITY OF COMPONENTS: COMPONENTS OF THE TURBINE STAGE

This diagram shows the overall failure probability results for the entire turbine stage plotted versus the operation time in years. The green curve is the probability that the disk fails due to crack growth. The brown curve is the probability that any of the 100 blades fails due to oxidation. The pink curve represents the probability that any of the 100 blades fail due to creep. Analogously, the blue curve is the probability that any of the 100 blades fail due to low cycle fatigue. The red curve is the probability that the turbine stage fails due to any of these component events, i.e. failure of the disk OR failure of any blade due to any failure mode. Obviously in this example here, the turbine stage as a system is driven only by a failure of the blades due to creep or LCF.

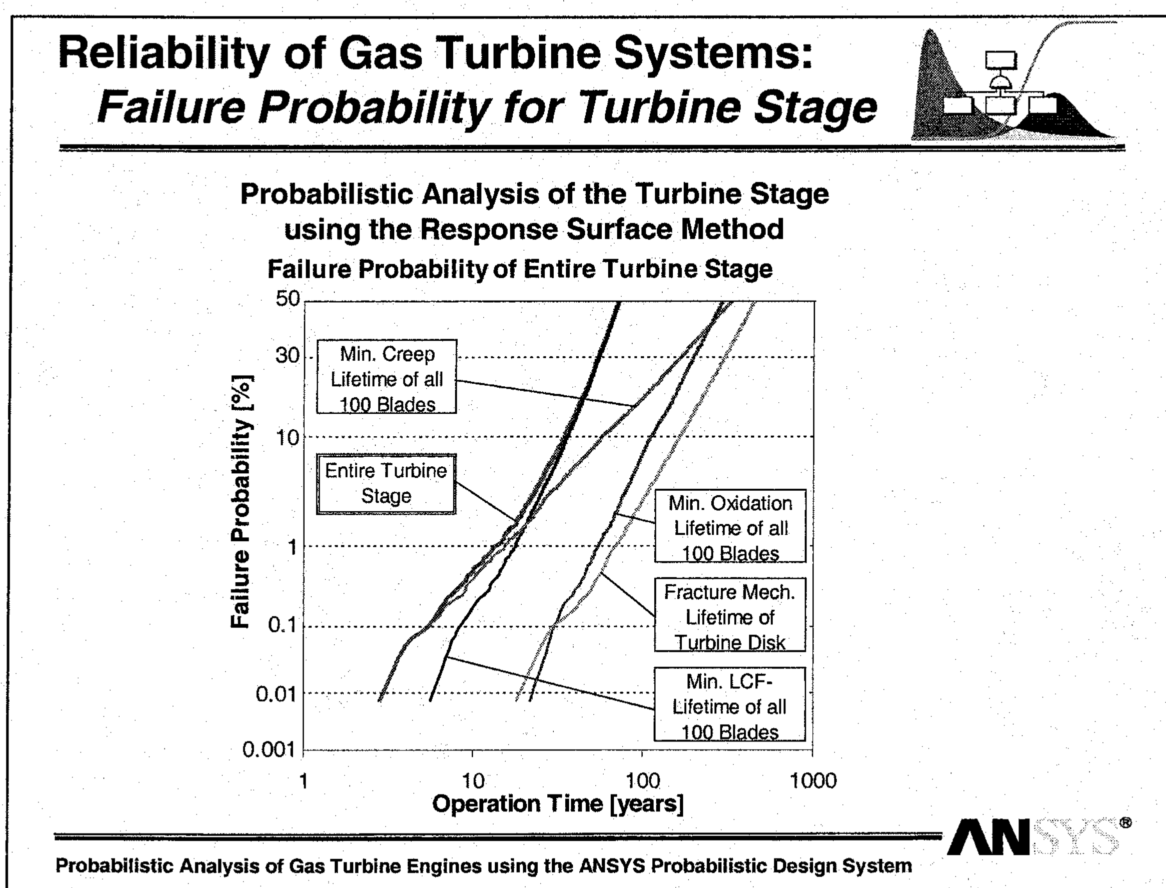


Figure 10

Airfoil Shape Optimization Under Uncertainty: Results for Expected Value Optimization and its Analytic Approximations

Dr. Luc Huyse
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RESEARCH OBJECTIVE

Deterministic optimization does not account for neither the inherent variability of the operating conditions nor the model uncertainties. The objective of this research is to adapt the existing optimization techniques to automatically include these effects. This results in more robust designs.

Research Objective

- Observation: use of mathematical optimization techniques frequently leads to designs whose performance is very sensitive to small fluctuations in the design model parameters.
- Some of these parameters can be highly variable or hard to estimate.
- Objective: adapt existing optimization techniques such that the solution becomes fairly insensitive to (minor) fluctuations in some or all of the mathematical model parameters.

Figure 1

DEFINITION OF ROBUST DESIGN

Robust optimization results in the design, which performs optimally under the variable (or uncertain) operating conditions over the entire lifetime of the design.

For this computation we assume there are no catastrophic failures; we are dealing with everyday fluctuations. This is quite different from reliability computations.

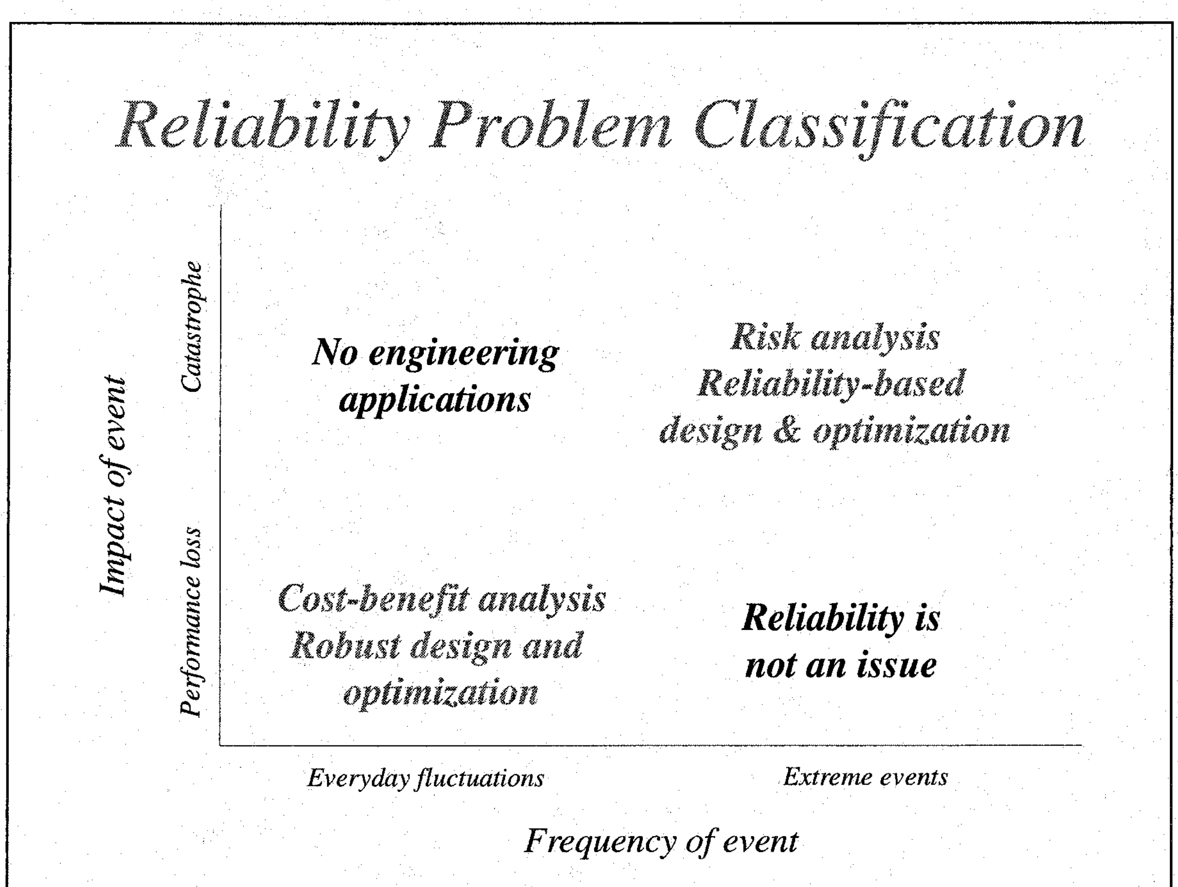

Figure 2

AIRFOIL GEOMETRY OPTIMIZATION

Find optimal airfoil geometry, which results in minimum drag C_d over a range of free flow Mach numbers M while maintaining a given lift $C_l^* = 0.6$. We start from a NACA-0012 airfoil.

For this example we assume a uniform distribution for the Mach numbers: $M \in [0.7, 0.8]$. All Mach numbers within this range are equally likely. The Mach number cannot fall outside this interval.

We solve the inviscid Euler equations using NASA's FUN2D code, which computes analytic derivatives. Far field boundary at 50 chord lengths.

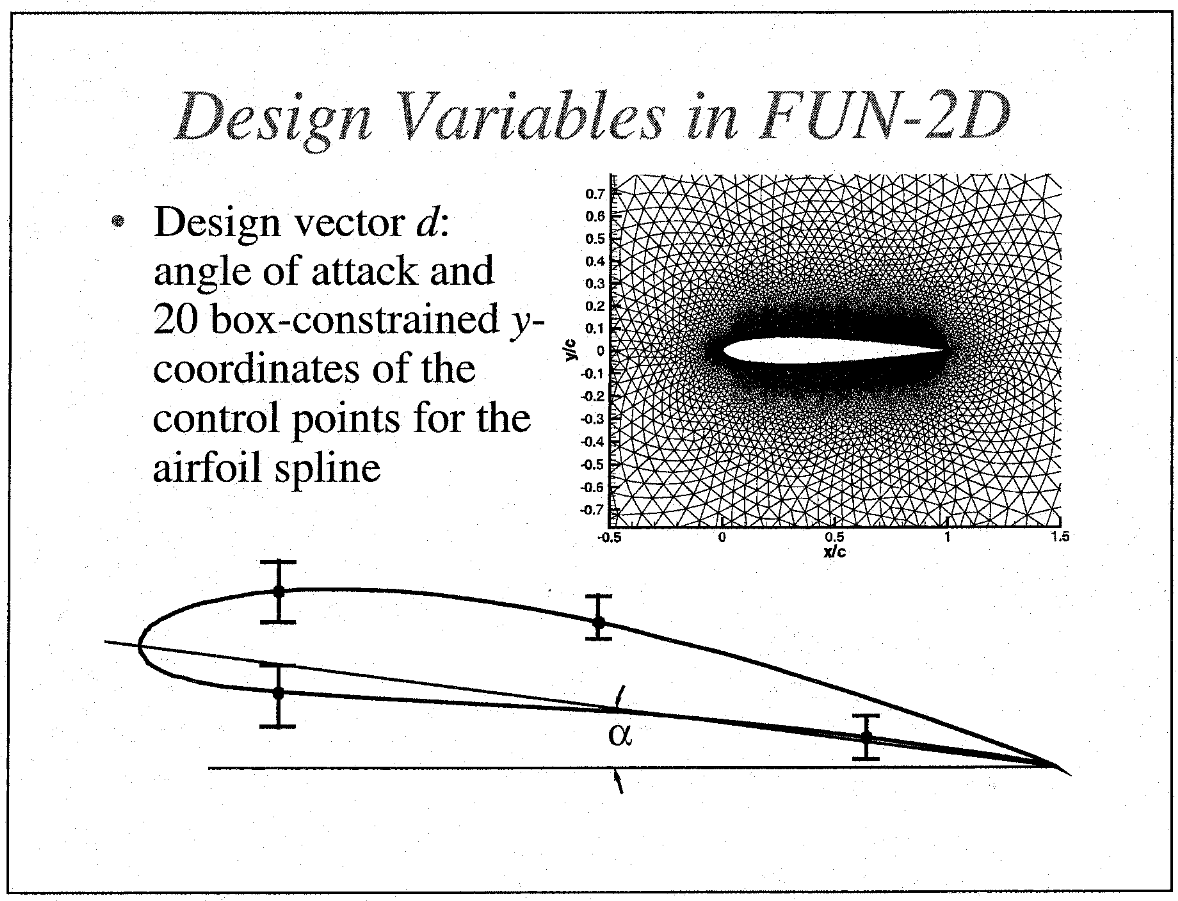

Figure 3

OPTIMIZATION FRAMEWORK

We used the ISIGHT framework, a product of Engineous Software, as the optimization engine. The framework provides an interactive high-level programming environment to define the optimization problem. It automates the communications between the user-provided analysis codes and the pre-programmed optimization routines.

iSight Optimization Framework

- Task Manager
- Process Integration
  - Parser for Input/Output files
  - Control structures
- Parameter Definition
  - Variables, objectives, constraints
- Optimization Plan
- Solution Monitor
  - Tracks all design variables during optimization

Figure 4

PROCESS INTEGRATION

The data flow during the optimization process is defined in the Process Integrator that includes several control structures and statements (IF, WHILE, LOOP). The flow is built up using a GUI, or can be implemented directly in the MDOL language.

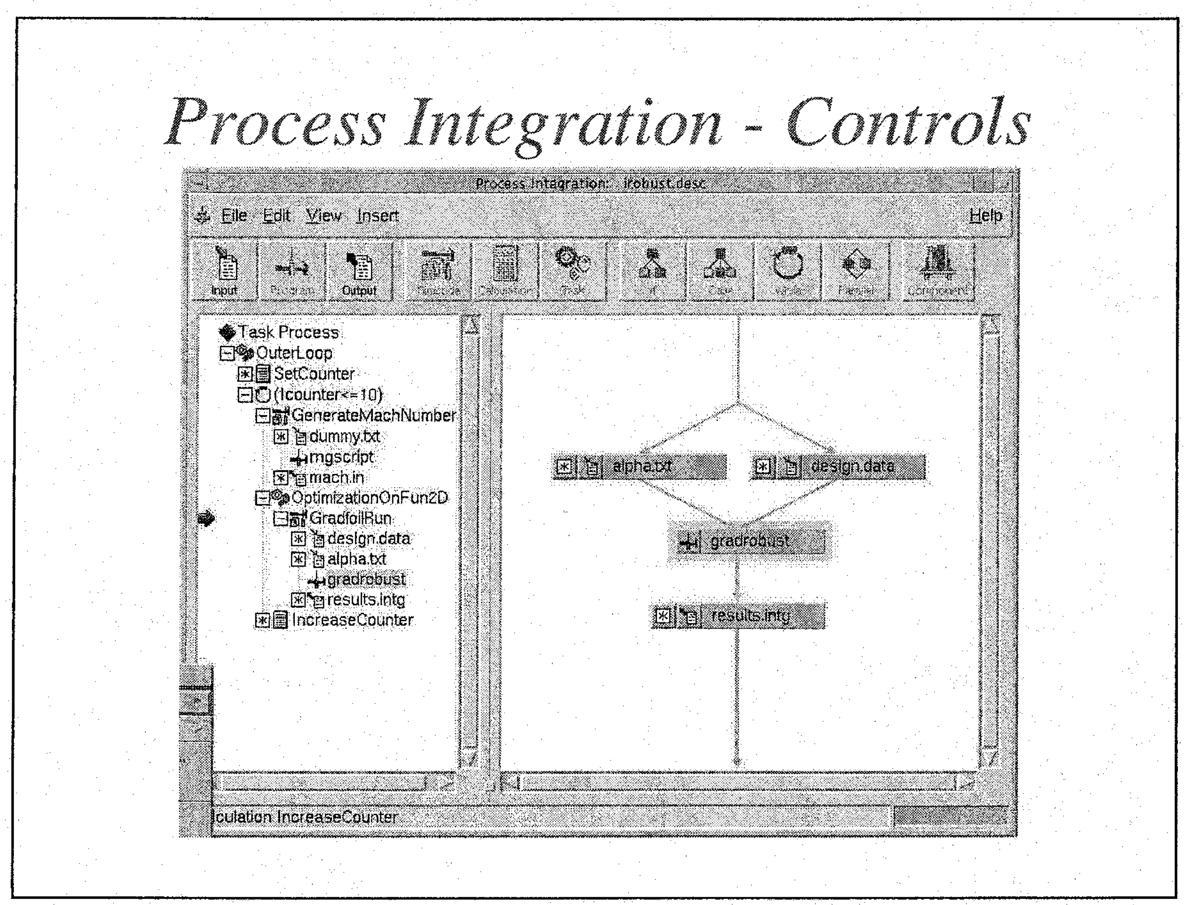

Figure 5

INPUT – OUTPUT

The built-in optimization routines communicate with customer software using input and output files. The Parser commands can be provided directly using the MDOL syntax, or can be generated by iSight using the provided GUI.

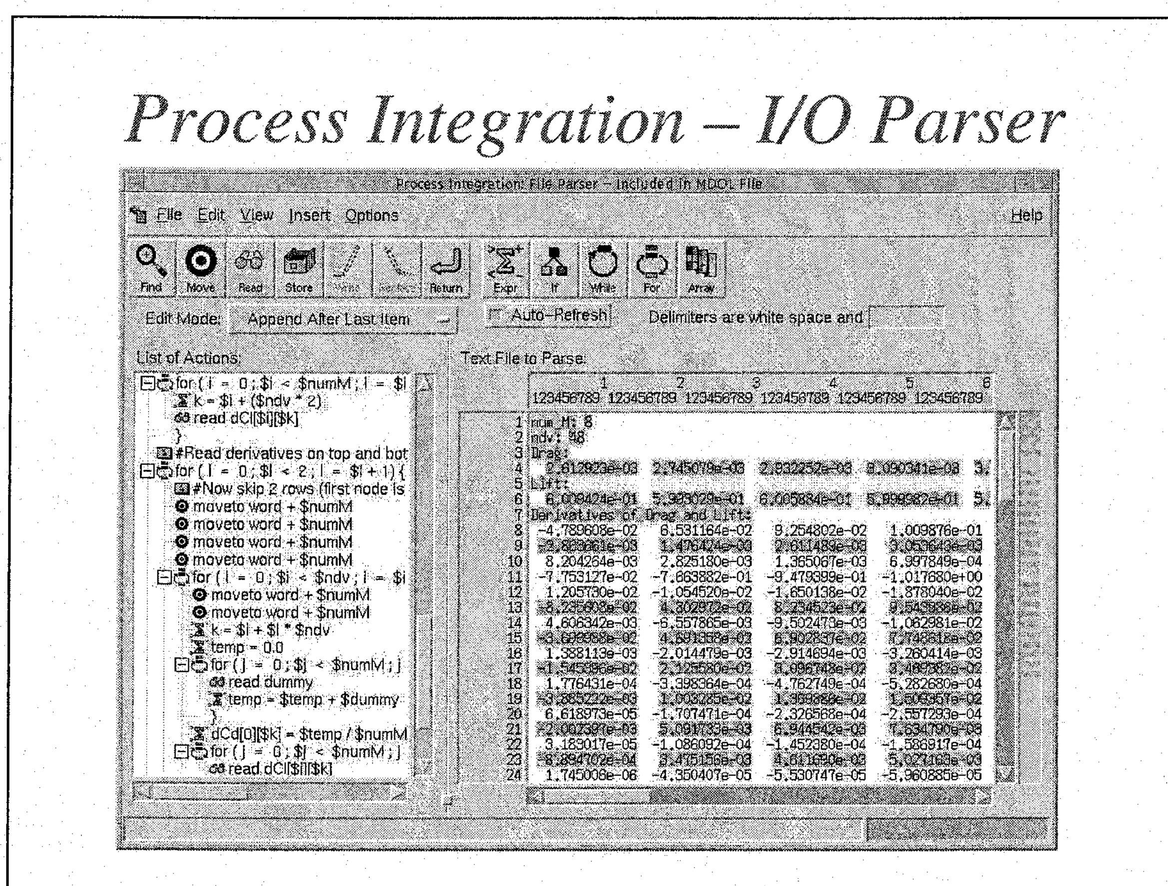

Figure 6

MODEL PARAMETER DEFINITIONS

Independent variables, objective functions and constraints are specified in the Parameter Definition module. Simple bounds can easily be included for the independent design variables.

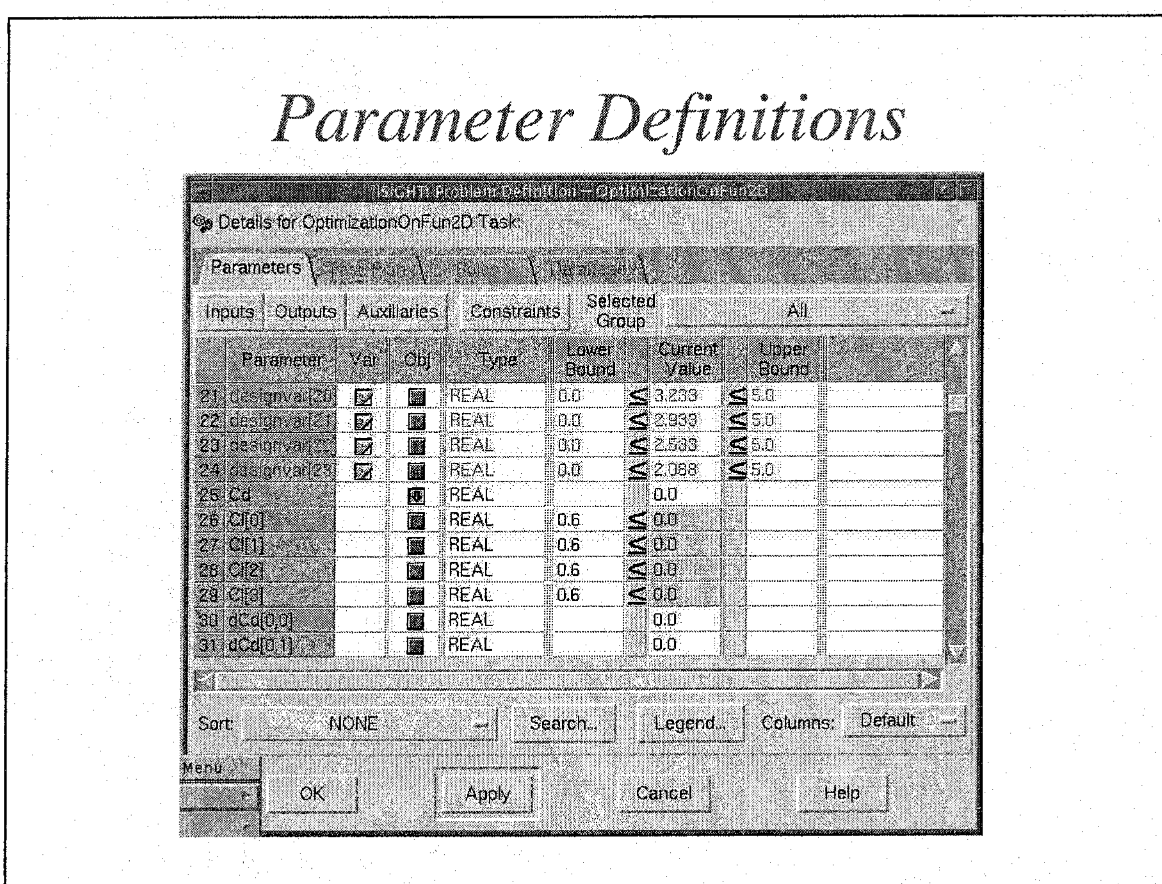

Figure 7

OPTIMIZATION ROUTINES

Several Optimization routines are built-in. We made use of the Modified Method of feasible Directions (CONMIN) and Sequential Linear Programming (based on ADS routines).

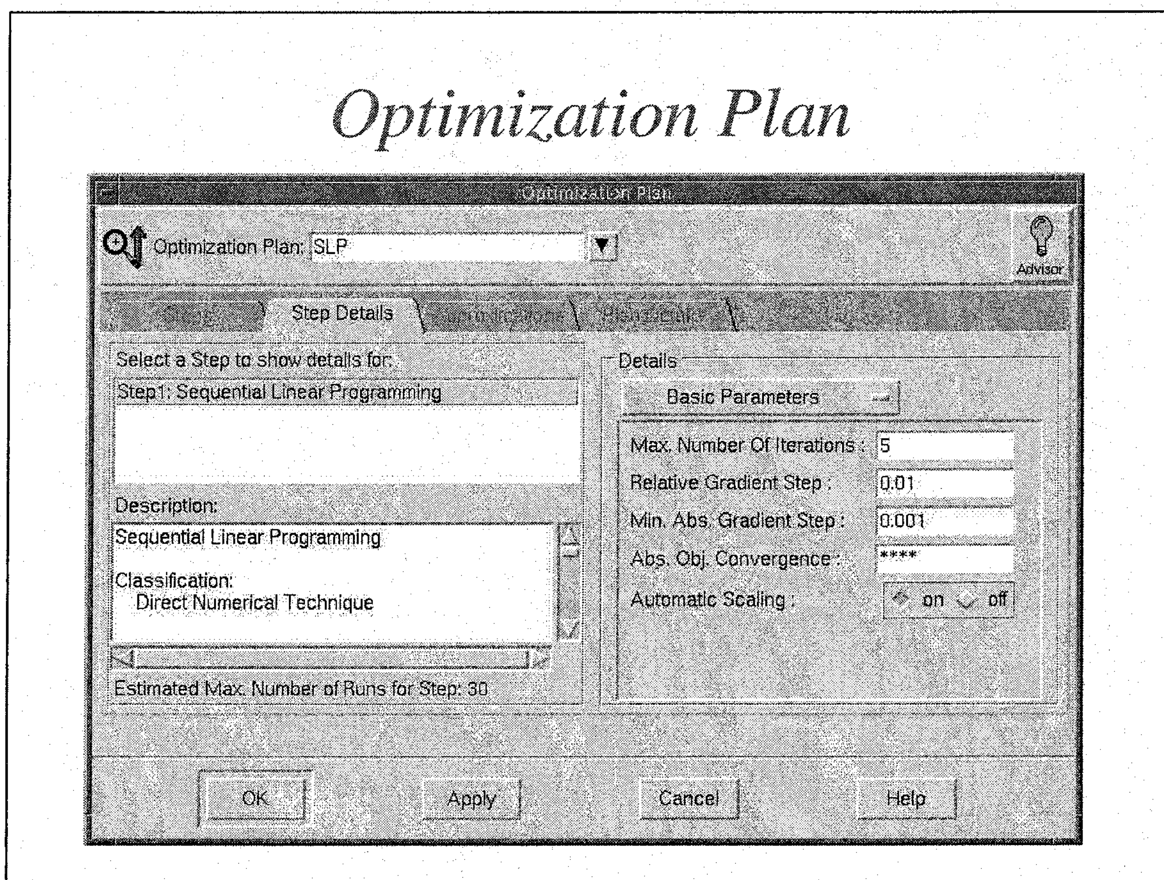

Figure 8

RESULTS MONITOR

All intermediate results of the optimization process are stored in a database. The results monitor displays the optimization histories in real-time. Here we show the optimization history for a drag-objective.

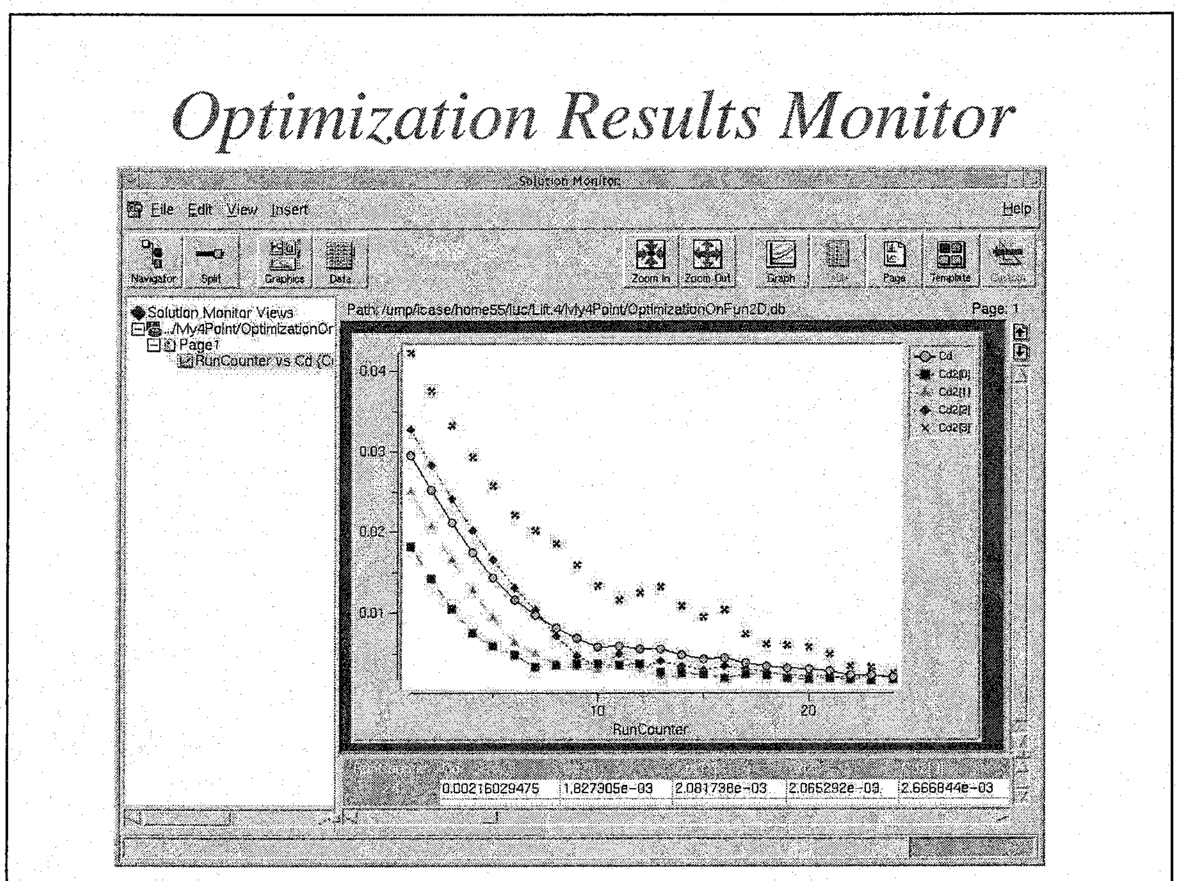

Figure 9

We highlight two methods: single-point and multi-point optimization

Single Design-Point Optimization

- The design vector *d* (geometry and angle of attack) is the only variable in the objective
- Fix all other model parameters at their design value. We consider only 1 free flow Mach number $M = M_{design}$ (*e.g. average Mach number during cruise stage*):

$$\begin{cases} \min\limits_{d \in D} & C_d(d, M_{design}) \\ \text{subject to} & C_l(d, M_{design}) \geq C_l^* \end{cases}$$

Figure 10

PROBLEMS WITH SINGLE-POINT OPTIMIZATION

Not clear which point to select as design point. The mean value is not a good choice for the design point when the model is highly non-linear.

Even though we are trying to push out M_{DIV}, the highest Mach number ($M = 0.8$) is not necessarily the best design point either.

The impact of fluctuations of the model parameters (due to either inherent variability or model uncertainty) on the response is completely unknown. The optimized design may actually perform worse under such "off-design point" operating conditions.

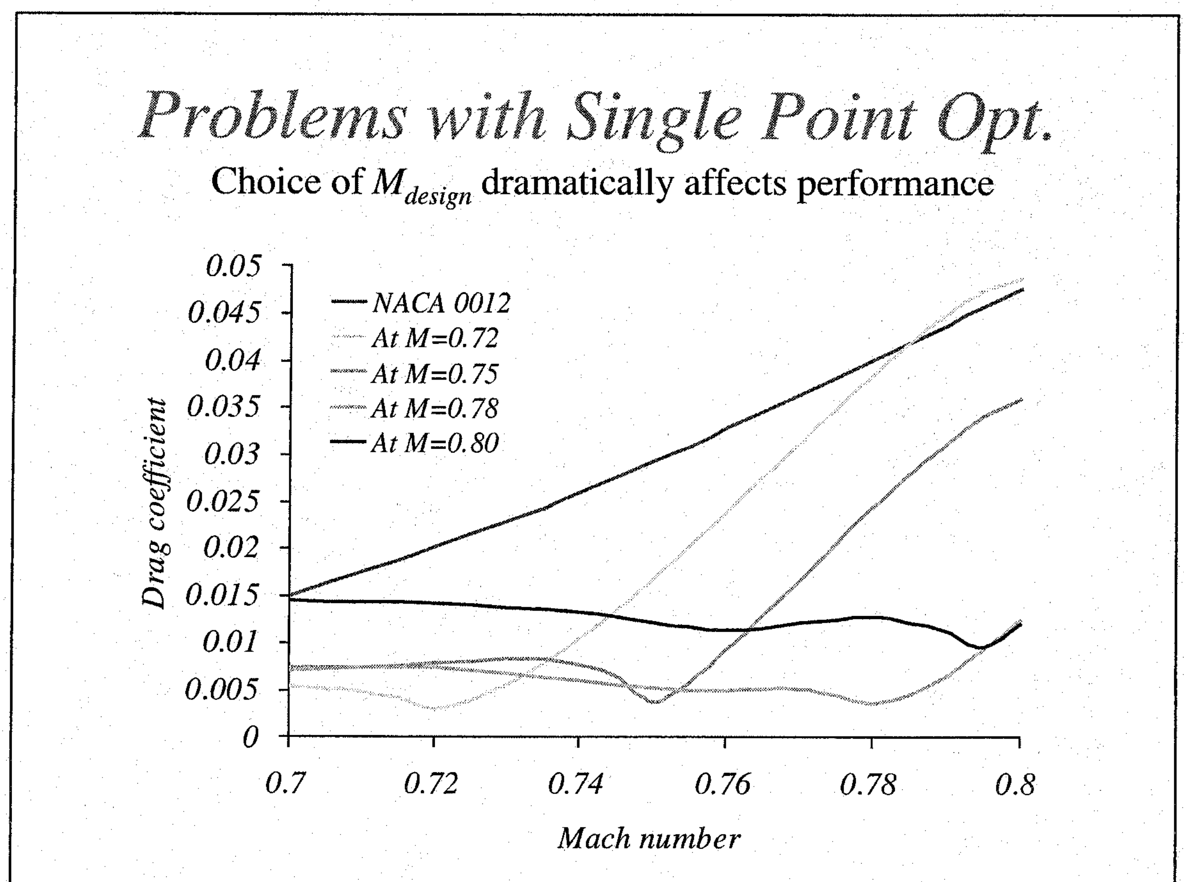

Figure 11

MULTI-POINT OPTIMIZATION

Attempt to overcome difficulties of single-point optimization by including several design operating conditions in the objective function

Multi-Point Optimization

- The design vector *d* (geometry and angle of attack) is the only variable in the objective
- Consider multiple design conditions at selected values of the free flow Mach number
- Objective function is a weighted average of all these design conditions

$$\begin{cases} \min\limits_{d \in D} \quad \sum\limits_{i=1}^{n} w_i C_d(d, M_i) \\ \text{subject to} \quad C_l(d, M_i) \geq C_l^* \quad \text{for} \quad i = 1, n \end{cases}$$

Figure 12

PROBLEMS WITH MULTI-POINT OPTIMIZATION

The resulting drag profile is sensitive to the choice of Mach numbers. It is not clear how to decide which Mach numbers to include in the objective.

What is the appropriate weight for each design condition (i.e. Mach number) in the overall linear combination?

Multiple drag troughs can be observed, one at each sample point.

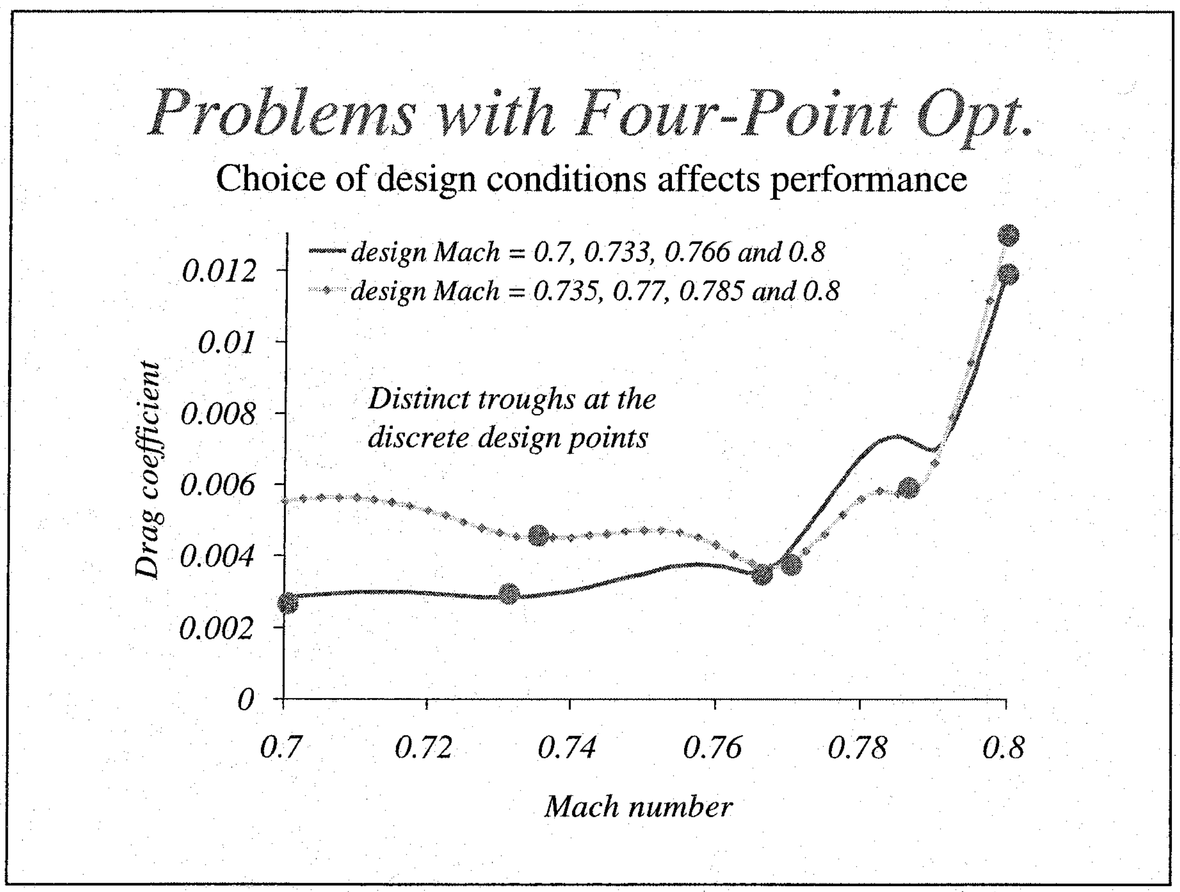

Figure 13

STOCHASTIC OPTIMIZATION

We seek to maximize the expected performance over all possible operating conditions.

Stochastic Optimization

- Modify the objective to directly incorporate the effects of model uncertainties on the design performance
- Highlight 2 methods:
  - Expected Value Optimization
  - Second-Order Approximate Results

Figure 14

STOCHASTIC OPTIMIZATION USING DECISION TREES

Consider all possible designs d_i and set up a decision tree.

Model all uncertain variables using (Joint) Probability Density Functions

The objective is to minimize the drag over the entire Mach range.

This shows that the best decision (or design) is the one that minimizes the expected value of the drag C_d with respect to M.

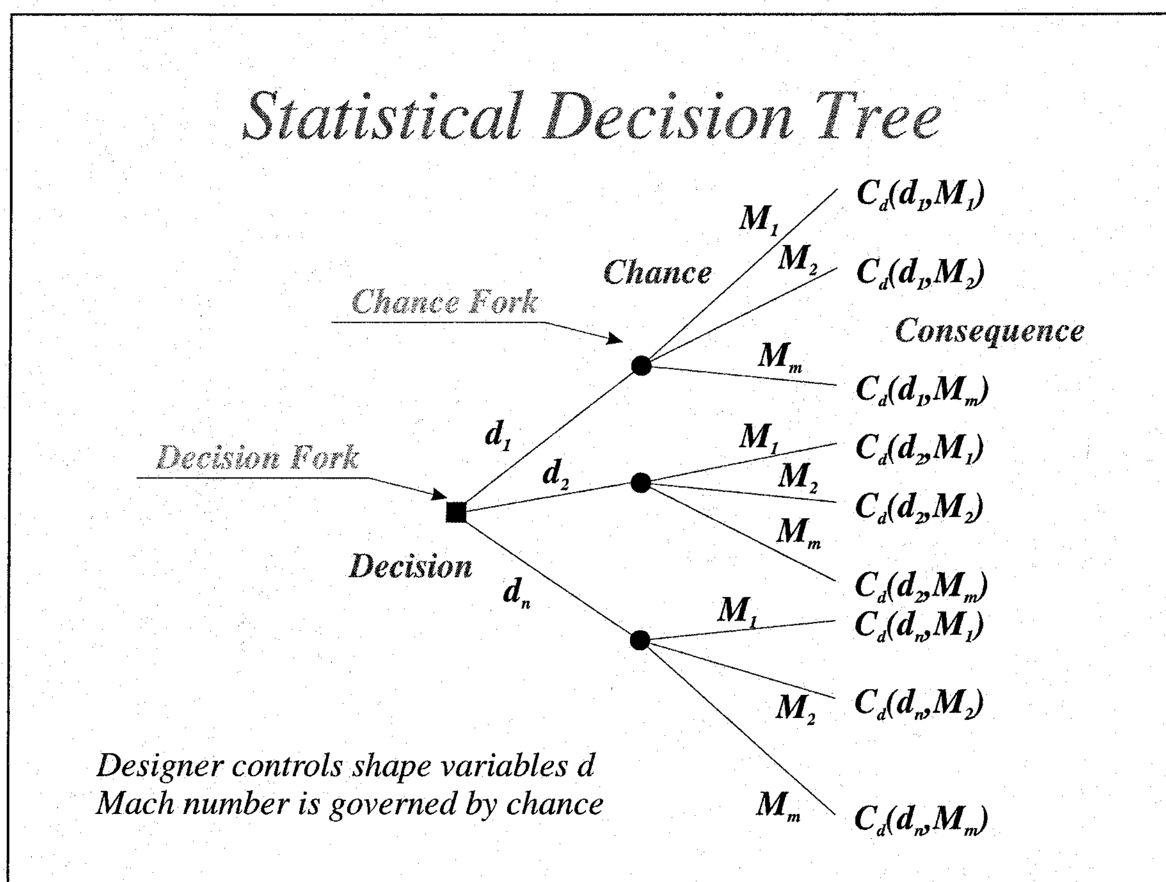

Figure 15

MATHEMATICAL FORMULATION

The objective in the optimization process is given by the expected value of the drag with respect to all possible operating conditions. We integrate the product of the drag function C_d and the probability density function of the Mach number

Mathematical Formulation

Minimize the expected value of the drag over the design lifetime:

$$\min_{d \in D} E_M\big(C_d(d,M)\big) = \min_{d \in D} \int_M C_d(d,M) f_M(M)\,dM$$

C_d is drag function

d is design vector (geometry, angle of attack)

M is uncertain parameter (Mach number)

f_M is Probability Density Function of Mach number

Figure 16

APPLICATION TO AIRFOIL PROBLEM

The design variables are the geometry of the airfoil. The angle of attack is a control variable. The angle of attack will be adjusted to achieve the required lift when the Mach number fluctuates. Here we only model slowly varying Mach numbers so that the constraint remains deterministic. Probabilistic constraints will be considered in a future study.

Application to Airfoil Problem

- Integrate over the uncertain parameter *M*, compute the expected value of C_d with respect to the free flow Mach number *M*.
- Minimize this integrated objective with respect to the design vector *d*.
- Actual flight data are readily incorporated in the probability density function $f_M(M)$

$$\begin{cases} \min\limits_{d \in D} & \int_M C_d(d, M) f_M(M) dM \\ \text{subject to} & C_l \geq C_l^* \end{cases}$$

Figure 17

SECOND-ORDER SECOND-MOMENT APPROXIMATION

When the objective function is approximated by a second-order Taylor series expansion, an analytic evaluation of the integral can be performed. This leads to a deterministic equivalent of the stochastic optimization problem.

SOSM Approximation

Approximate objective by second-order Taylor series expansion about the mean value of M, and evaluate the expectation integral analytically.

$$\min_{d \in D} \int_M C_d(d, M) f_M(M) dM \cong$$

$$\min_{d \in D} \left[C_d(d, \overline{M}) + \tfrac{1}{2} Var(M) \frac{\partial^2 C_d}{\partial M^2} \bigg|_{M=\overline{M}} \right]$$

$$\textit{subject to}: \quad C_l \geq C_l^*$$

Figure 18

EFFECT OF SOSM CORRECTION

Second-Order information represents curvature of C_d-M curve.

The weighting between drag and design point and curvature depends on the variance of the Mach number.

With SOSM method the drag is not reduced quite as much as for single point design but the drag is much less sensitive to variations in the Mach number. The drag trough is avoided, no "over-optimization".

Second-Order derivatives were computed using finite differencing of first-order derivatives. This introduces numerical noise in the derivative and may "confuse" the optimization algorithm.

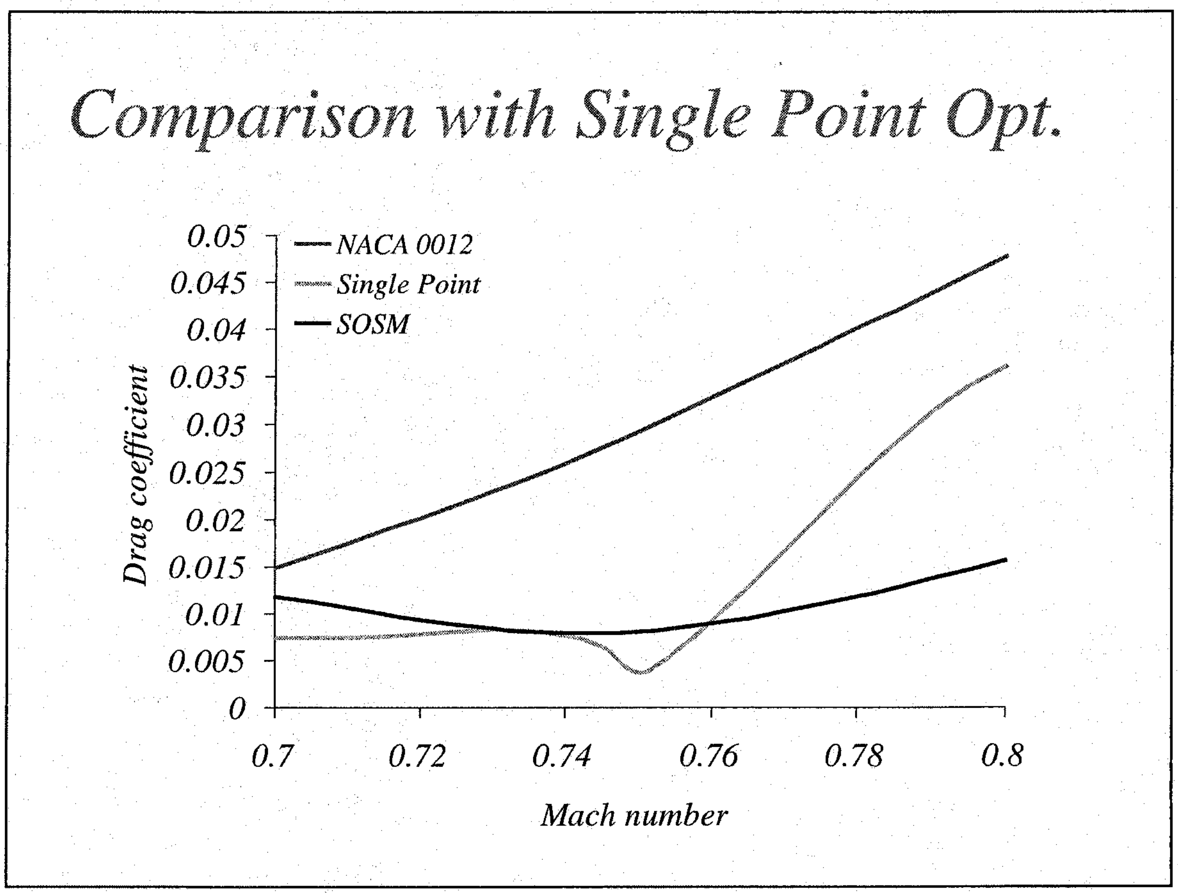

Figure 19

EXPECTED VALUE OPTIMIZATION

Here we use a numerical integration procedure to perform the integration of the objective function during each optimization step. This is computationally more expensive but also more accurate.

Direct Evaluation of Integral

- Evaluate integral directly using a numerical integration method.
- To avoid over-optimization, make sure you select different integration points for each optimization step.
- We used 4 point integration with random selection of integration points.

Figure 20

ADVANTAGES OF EXPECTED VALUE OPTIMIZATION

Robust design consistently has smallest expected value (up to accuracy of integration).

There is no need to arbitrarily select design conditions (i.e. Mach numbers) or weights any longer because we integrate over the PDF of the operating conditions.

Drag troughs are reduced and do not occur at integration points any longer.

Additional model uncertainties can be accounted for as well by extending the integration over the uncertain model parameters.

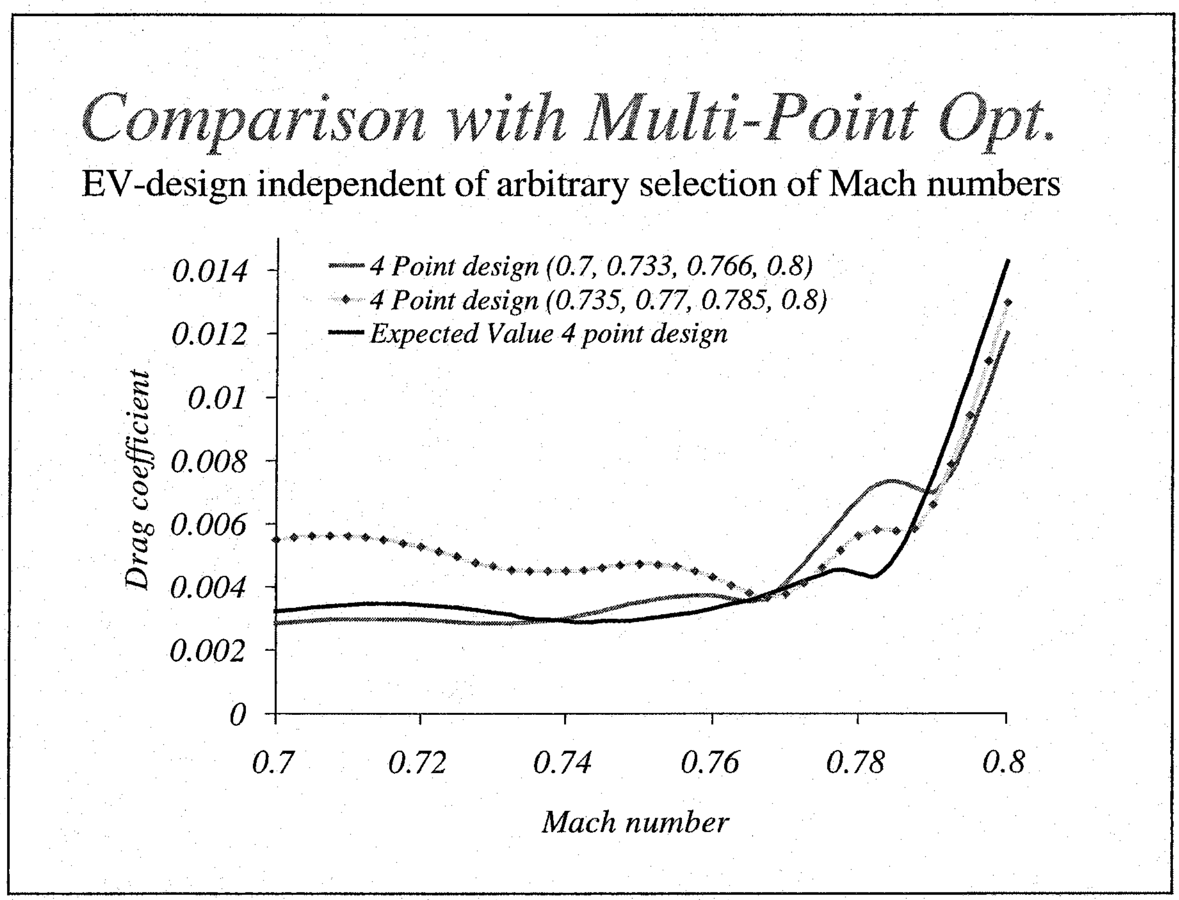

Figure 21

COMPUTATIONAL EFFORT

SOSM Method replaces integration with a second-derivative evaluation. If accurate higher-order derivatives can be computed, this method results in significant computational savings over the full integration.

SOSM scales linearly with the number of uncertain variables, while integration algorithms generally follow a power law.

Relative Computational Effort

Optimization Method	1 Random Variable	3 Random Variables
Single-Point	1	1
SOSM(*)	3	7
Expected Value (4pts)	4	64

(*) Less if analytic derivatives are available

Figure 22

ASSUMPTION OF PDF

For bounded Mach-intervals a Beta-distribution seems appropriate. The Beta PDF can represent a variety of shapes (symmetric or not, bathtub...). For unbounded distributions a detailed analysis of the tails is required.

Here we show several assumptions for the PDF, and will assess their impact on the optimal drag-rise curve.

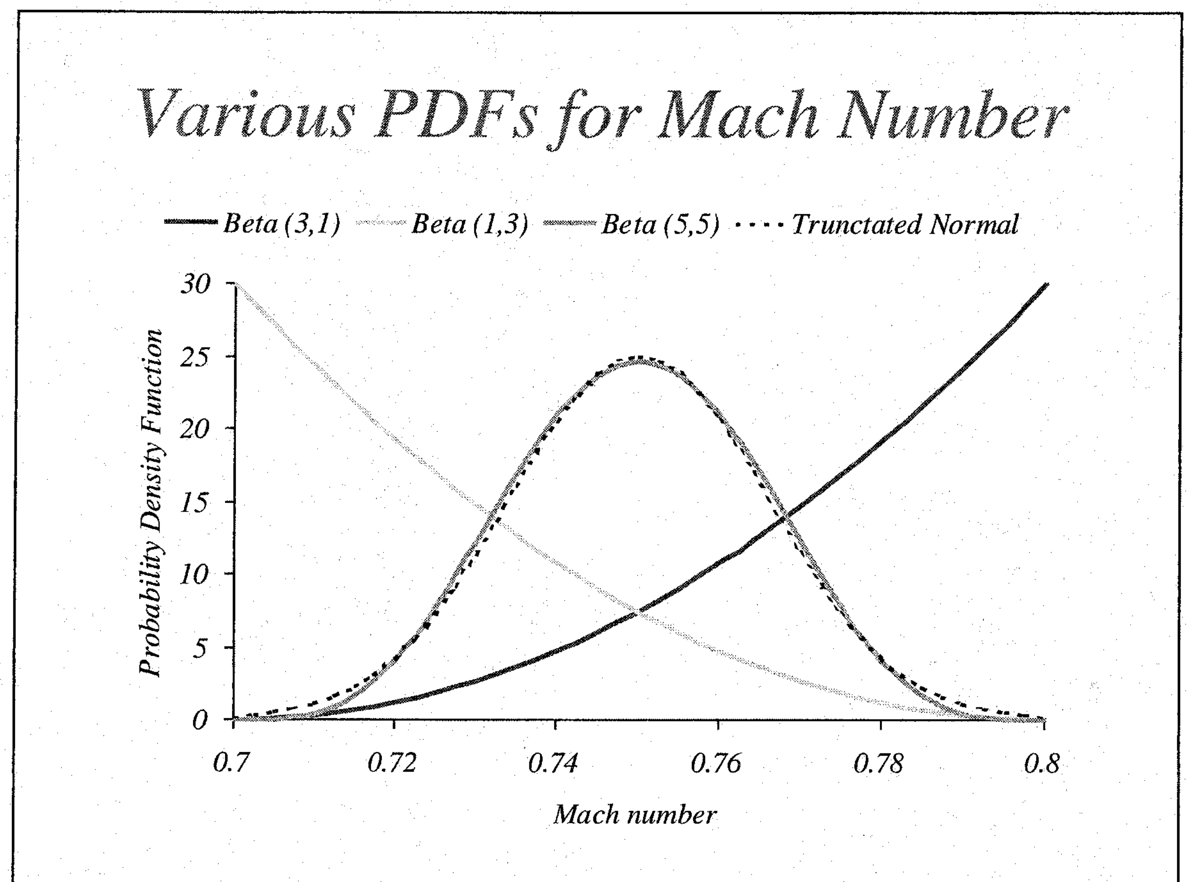

Figure 23

IMPACT OF PDF

The Expected Value Optimization results automatically reflect the relative importance of each of the Mach numbers. Depending on the relative likelihood of the Mach number (shown in previous slide), the drag is reduced to a larger or smaller extent. This shows that the optimal drag-rise curve depends on the probability density of the Mach number.

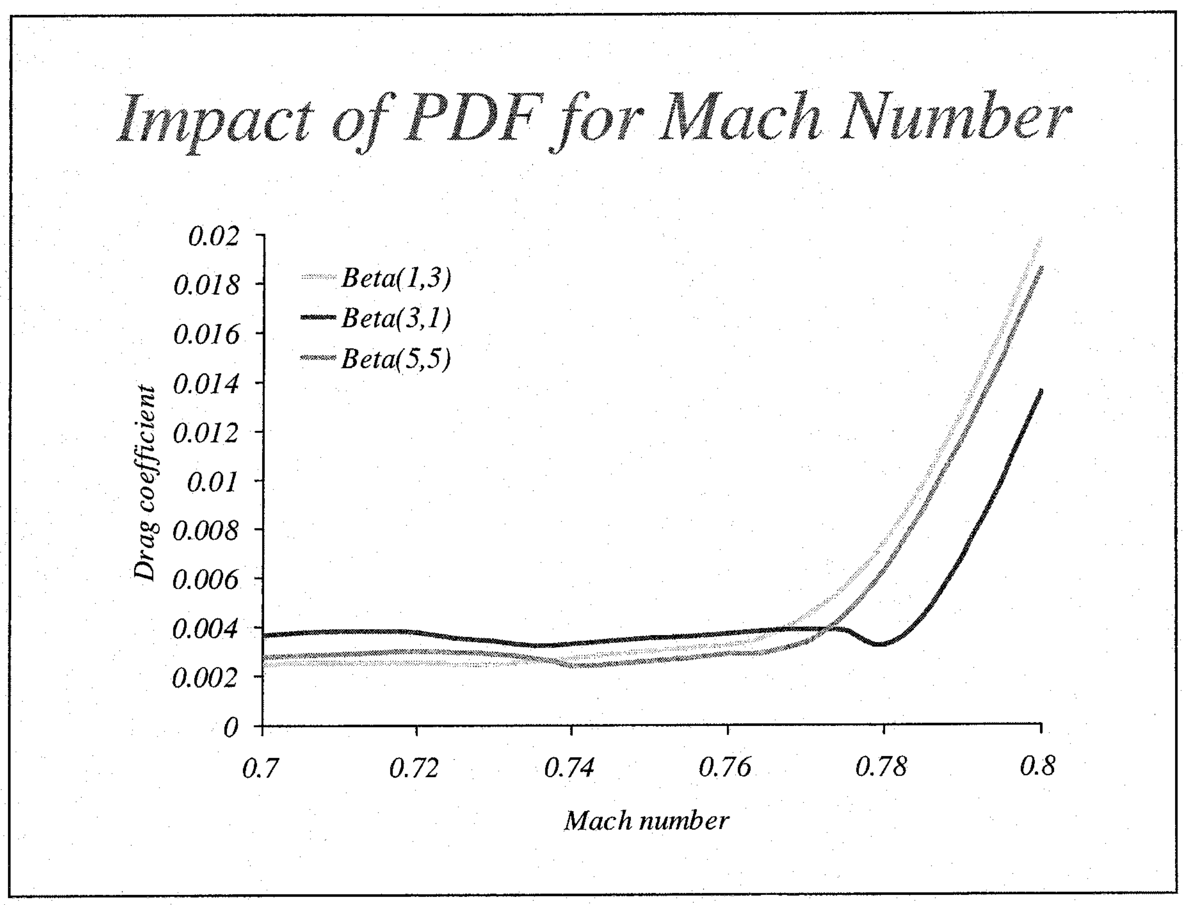

Figure 24

FURTHER WORK AND SUMMARY

In future research we will extend the method to include effects of other uncertainties besides the Mach number; preferably using faster integration techniques (adaptive sampling). We will also include probabilistic constraints.

Conclusions

- Statistical decision theory indicates that minimizing the expected drag over the lifetime leads to the optimal robust design. This removes the arbitrariness from the selection of the design conditions and/or weights, which is found in multi-point optimization.
- SOSM shows considerable improvement in the robustness of the design compared to single-point.
- The SOSM analytical approximation shows that, at the mean Mach number, the first-order sensitivity does not affect the expected value of the design.

Figure 25

An Overview of the Robust Design Computational System (RDCS) A Collection of Tools to Enable Low Risk Designs

Dr. Kadambi R. Rajagopal
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The Boeing Company
Canoga Park, CA 91309

AN OVERVIEW

The initial version of the Robust Design Computational System (RDCS) was developed as a cooperative effort between DARPA, The Boeing Company, The Ford Motor Company and MacNeal Schwendler Corporation during 1996 -1999. Since then the product is continually being enhanced using BOEING internal funds. The RDCS product is being used internally within Boeing at several sites. A commercial version of the product called MSC.Robust Design is being marketed by MSC software as part of engineering service engagements.

An Overview of the Robust Design Computational System (RDCS)
A Collection of Tools To Enable Low Risk Designs

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Training Workshop on Nondeterministic Approaches and Their Potential for Aerospace Systems
May 30 - 31, 2001
NASA Langley Research Center
Hampton, Virginia

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Figure 1

FUNDAMENTALS THAT DROVE THE RDCS DEVELOPMENT – THE LAUNCH MARKET BUSINESS CASE

In the following few slides I set the background reasons why the RDCS system was developed with its implemented features. It is based on a sound business case.

Before the 80's the DOD and NASA programs the emphasis was on performance. But the budgetary pressures, the global competition and meeting the increasing demand by product customers for performance at an affordable cost with out sacrificing reliability became a paramount goal. The engineers at the working level are now schooled, lectured and admonished to be sensitive and responsive to total life cycle cost issues. The difference can be between having a program and not having one. Experts might argue on the order of faster, cheaper and better but all three elements are needed.

Fundamentals that Drove the RDCS Development
The Launch Market Business Case

- **Cost is an independent variable**
- **Increased emphasis on performance at an affordable cost**
- **The competition is global**
- **Customer satisfaction demands robust products with high quality and reliability**
- **Time to market is critical**

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Figure 2

LOW-COST DEVELOPMENT CAPABILITY NEEDED

Consider the development cost of major products in different industries such as rocket propulsion, automobile and jet engines. The schedule and cost are dominated by the "Test Fail Fix" design methodology. That is, there is heavy reliance on test to meet the high reliability and performance goals. This has been a proven approach that has produced reliable products, but the cost is not consistent with the new accelerated schedule and cost goals. So how what can we do differently?

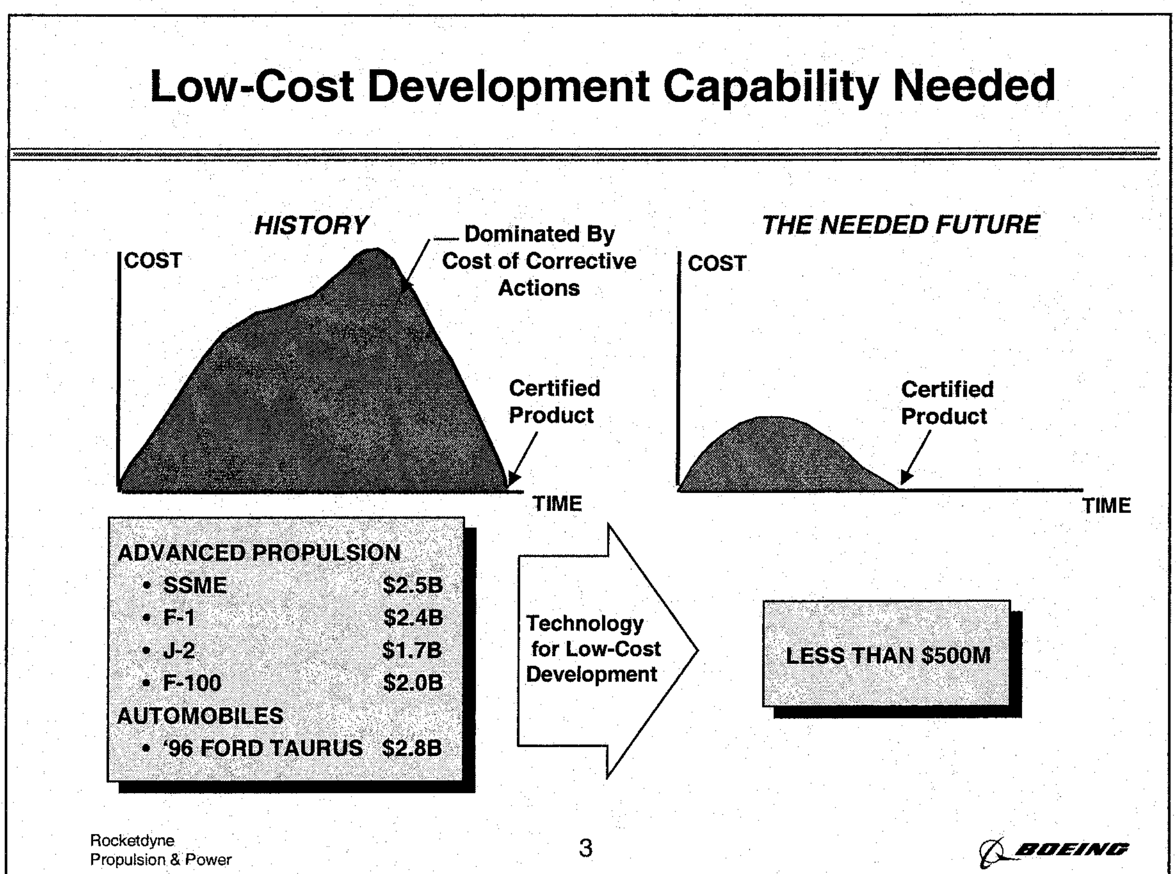

Figure 3

FUNDAMENTALS THAT DROVE THE RDCS DEVELOPMENT – AEROSPACE DESIGN SHOP

Before we design a system, we need to look at the environment at which the DOD and NASA product design teams are operating. First of all we cannot afford to fail as the consequence of failure (cost) is very high. We live in a glass house. The rigors of low weight and high performance demand the use of cutting edge technologies. There is tremendous progress on the accuracy of numerical model prediction. This when combined with the computer revolution is providing us with an unprecedented opportunity to design the products right the first time. Any design framework that has the potential to provide a solution to this problem must consider the elements listed on this slide and design the system accordingly.

Fundamentals that Drove the RDCS Development
Aerospace Design Shop

- **Consequence of failure high**
  - **risk = f(probability of failure, cost of failure)**
- **Cutting edge technologies**
- **Compute intensive analysis**
- **Limited quantity or one of a kind hardware**
- **Weight critical**
- **Geographically dispersed design teams**

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Figure 4

FUNDAMENTALS THAT DROVE THE RDCS DEVELOPMENT – AUTOMATION VS. PROCESS IMPROVEMENT

There is a big difference between automation and a real design process improvement. Automation makes execution of the existing design processes faster. If a failure occurs automation will certainly help recover from the failure faster and cheaper, but what we want to aim is to have no failure in the first place. That requires changes and improvement in design quality and design process. It requires a paradigm shift.

Quality improvement in space products with an acceptable cost and reliability can not achieved with out considering variability in a very fundamental way in the design process.

Fundamentals that Drove the RDCS Development

Automation Vs Process Improvement

- **Automation is normally speeding up the design process**
  - **Traditional CAE**
  - **Partial but not the full answer**
- **Improvement in design quality requires a more fundamental change**
- **Quality is meeting contractual/customer expectations of the product performance consistently every time**
- **It is impossible to think quality improvement without considering variability**
- **Reliability is a significant attribute contributing to the quality**

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Figure 5

FUNDAMENTALS THAT DROVE THE RDCS DEVELOPMENT –A QUALITY SCENARIO

Robustness of a product should not be considered as a product with high margins. The reality of high performance and weight critical parts do not allow us that luxury very often. The robustness is defined here as a designed in quality of the product that makes it performance insensitive to variations.

All non-trivial design activities are trade off exercises. Consider the cartoon in this slide of one performance Vs one design variable scenario. The design problem is to choose a nominal design point in the presence of uncertainties or variations. The robust design choice cannot be made unless the variations are considered and then an intelligent design decision can be made. When we say we need to optimize the product performance, we need to set the objective such as "This product shall met the performance goal 99.99% of the time" which is a probabilistic optimization statement.

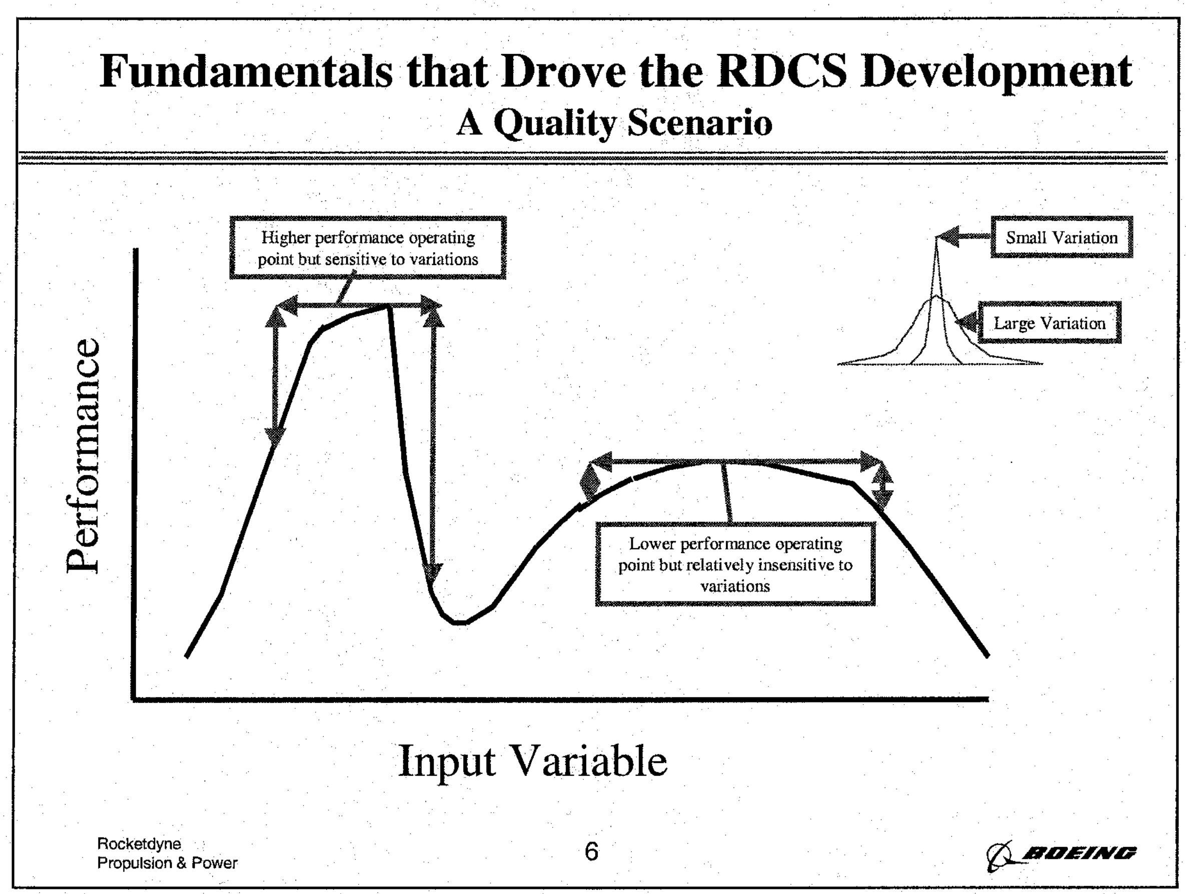

Figure 6

FUNDAMENTALS THAT DROVE THE RDCS DEVELOPMENT – MULTI-DISCIPLINARY APPROACH A MUST

Earlier efforts in the 80's were concentrated on single discipline approach to reliability estimation such as structural reliability. However, the source of component unreliability is driven from many sources such as manufacturing, process, inspection process, material property variations as well as load estimation from many other disciplines such as Thermal and fluid. Thus in order for a design system to be used on practical product design it must be capable of accommodating multi-disciplinary analysis. The multi-disciplinary definition should encompass traditional engineering models such as structures, thermal fluid etc. as well as models representing non-engineering functions such as cost models.

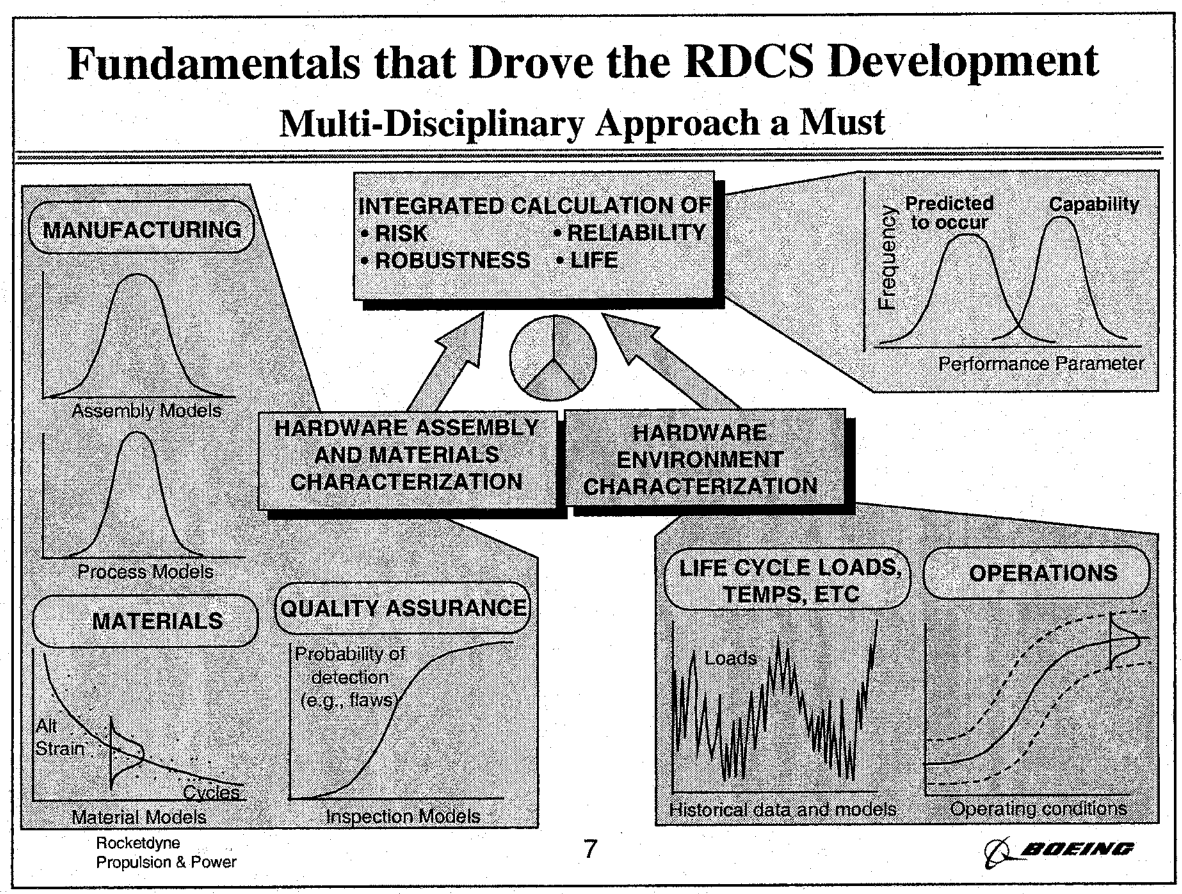

Figure 7

RELIABLE PRODUCE DESIGNS CAN BE ACHIEVED USING A VARIETY OF APPROACHES

The RDCS system enables robust designs in a variety of ways. Fundamentally, it allows the engineer to understand the design space in a systematic manner both in the deterministic as well as in the non-deterministic sense using a variety of tools. Efficiency in the problem statement, computations and user friendliness is of paramount importance.

Reliable Product Designs Can be Achieved Using a Variety of Approaches

- **A robust design is one wherein the operating point for the controllable design variables are optimized such that design performance measures are less sensitive to the random factors that affect the performance.**
- **A robust design can be achieved**
  - **By appropriately choosing the nominal design point that yields desired insensitivity to the random variables or**
  - **Controlling the variations in random variables by a tighter tolerance at an additional cost or**
  - **By a combination of both approaches**
- **RDCS helps achieve robust design**
  - **Provides tools that facilitates understanding of the design space in a systematic manner. (E.G sensitivity analysis, design scan, response surface)**
  - **Deterministic and probabilistic**

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Figure 8

REQUIREMENTS FOR A MODERN DESIGN FRAMEWORK

To meet the design process improvement needs, this slide summarizes the key attributes that a modern design framework should possess. It includes practical issues such as interfacing with existing analysis tools that the design shop is using with deterministic approaches. It is also important to have a robust distributed computing capability for compressing the analysis wall clock time. The framework should also provide a means to compare results from deterministic design approaches with newer non-deterministic approaches.

Requirements for a Modern Design Framework

- **It must have an architecture that is an enabler of**
  - **Exploring the design space**
  - **Automated design explorations**
  - **Multidisciplinary system models**
  - **Parametric concepts**
  - **Interfaces with COTS (commercial Off The shelf) and custom codes**
  - **Computational efficiency**
  - **Distributed collaborative computing/engineering**
  - **Suite of design procedures**
  - **Wide range of design tools from traditional past design practices to more modern design procedures**

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Figure 9

RDCS TOOL – AN INSTANCE OF MODERN DESIGN FRAMEWORK

The RDCS architecture cleanly separates the key elements of the design task to meet the objectives discussed earlier. The domain specific computational models are defined in the mathematical models (can be a network of multi-disciplinary models). The design processes contain views and associated algorithms that enable the engineer to understand the design problem in a variety of ways. They allow the engineer to cut and slice the design space to under stand the design problem efficiently. It is important to recognize that theses design process views and algorithms are completely generic and have no math model domain intelligence in them. The system director provides the communication interface between the three elements.

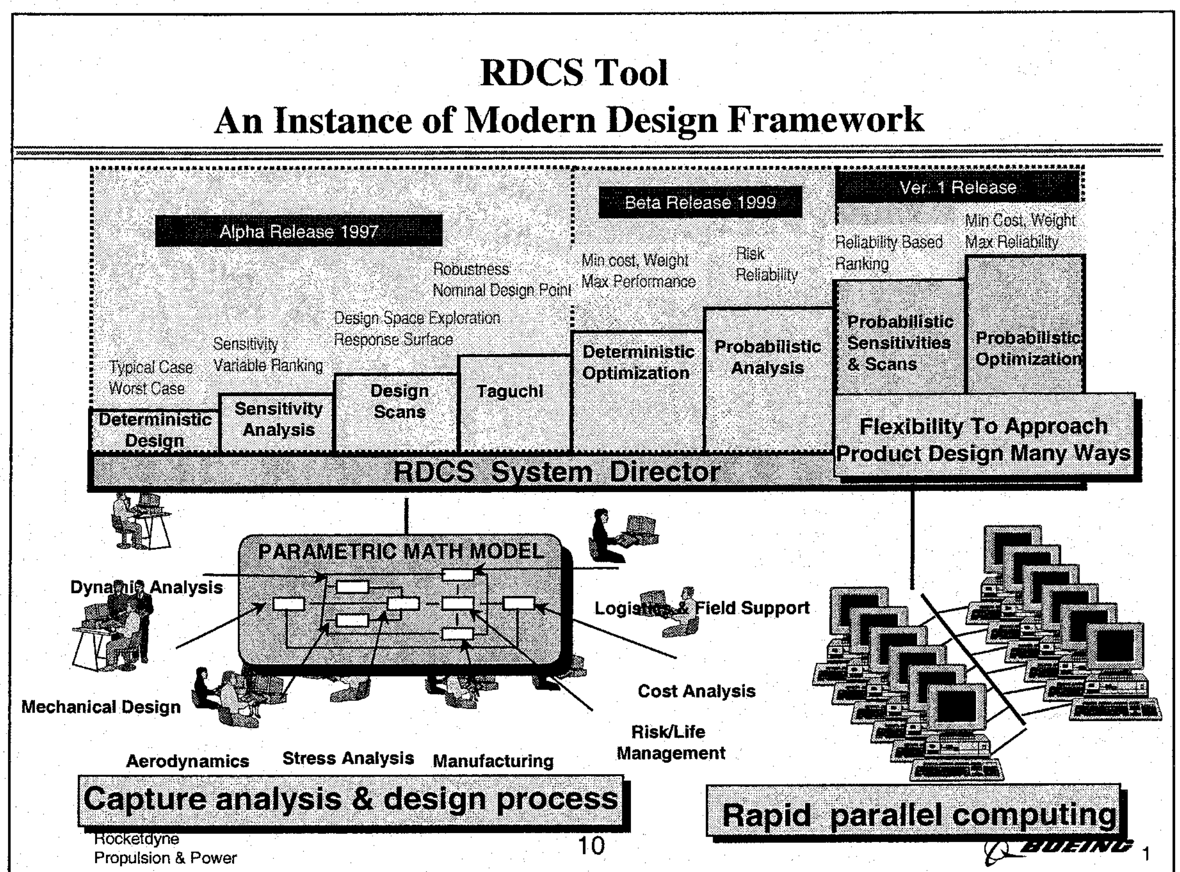

Figure 10

DESIGN SPACE IS SAME FOR ALL THE DESIGN PROCESSES

In the past, sensitivity analysis, parametric analysis, design of experiments using full and fractional factorial designs, probabilistic analysis either Monte Carlo simulation or First or Second Order Reliability Methods, Optimization, Taguchi Methods etc. were viewed as independent approaches to product design using separate computer programs. This slide highlights that all the design approaches are trying to solve the same design problem but with a different sampling approach of the design space. Of course the analysis of information have different approaches.

A single design framework that integrates and implements all approaches has significant advantages. This integrated approach provides opportunities for avoiding wasteful duplication in input preparation work, allows exploitation of synergy between approaches using common compute modules, sharing results between deign processes to avoid redundant or duplicate computations. The results are improved overall efficiency in computations as well as quantum leap in design knowledge gained.

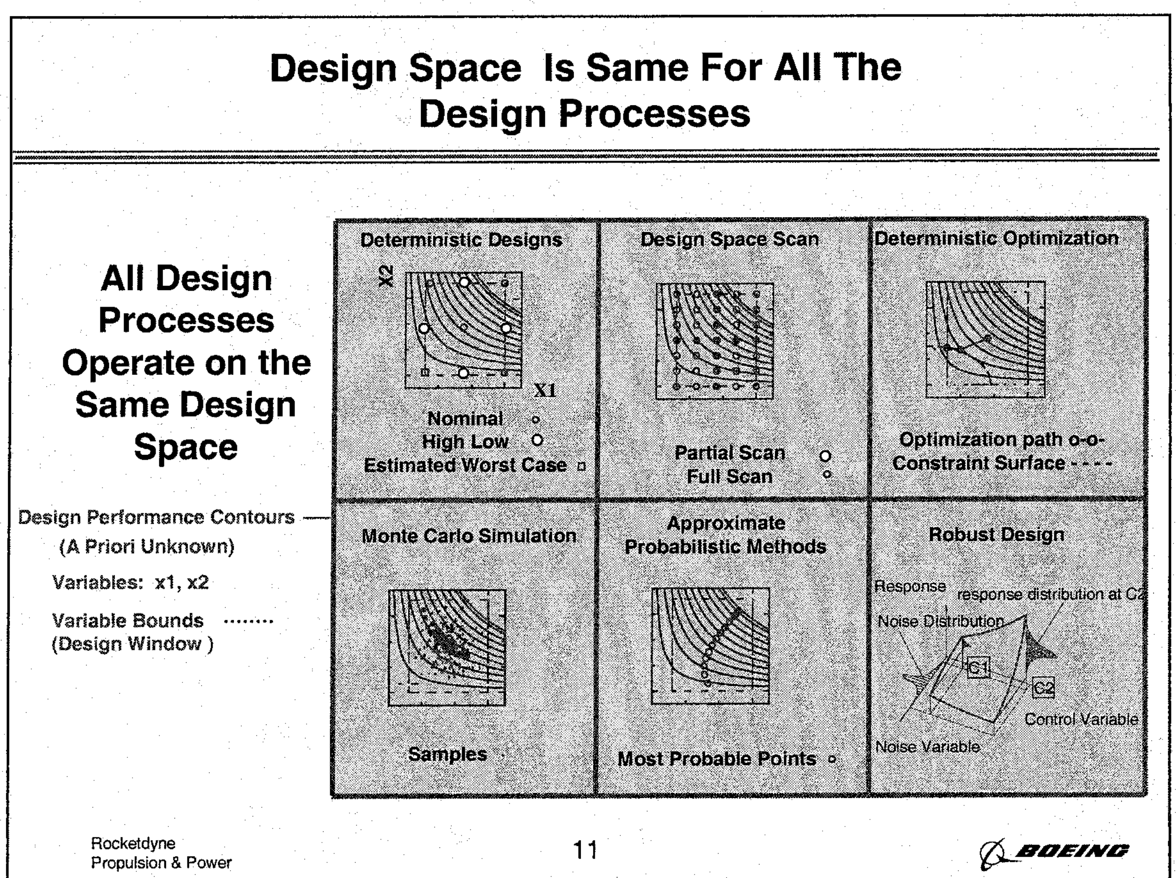

Figure 11

AVAILABLE OPTIONS AND TOOLS WITHIN RDCS

The RDCS system is one instance of such a modern design framework with probably many more frameworks to come in the future. These frameworks when implemented with a clean architecture that separates the tasks (as earlier discussed), addition of new yet unknown design processes in to the frame work should be an easy matter. In order for these frame works to be used in the design shops, easy graphic user interfaces to input as well as to post process the results is a must. They should further encapsulate the complexities of the analysis and the technologies they represent.

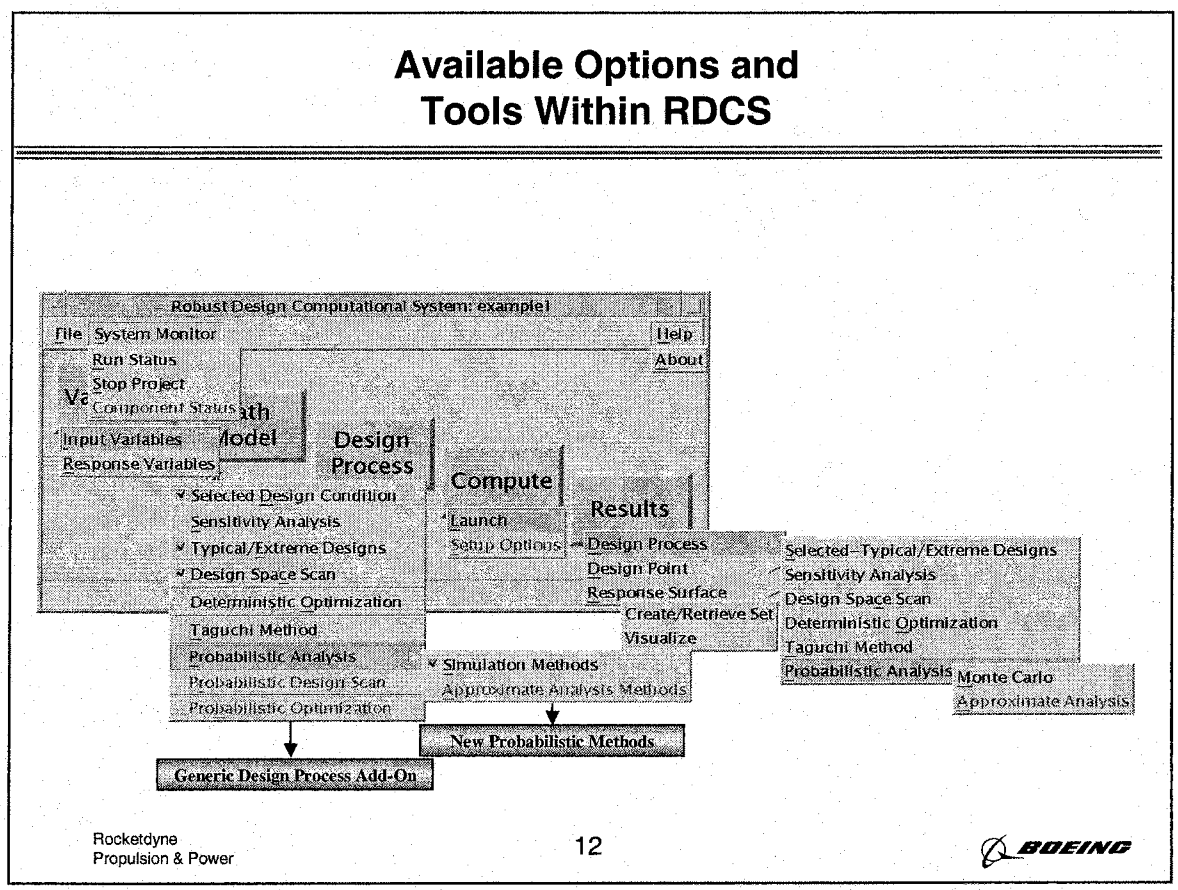

Figure 12

WHY DO WE NEED DISTRIBUTED COMPUTING?

The systematic exploration of the design space with many different design process views comes with a price, increased computational load. The number of cases or analysis that need to performed can be one to several orders of magnitude greater than single one worst case analysis. However, we are in the midst of a computer revolution wherein the cost of computing has gone down significantly. Software that implements a robust distributed computing technology wherein hundreds of cases can be run in parallel can make a significant difference in the use of these technologies in a schedule driven product design shop.

Why Do We Need Distributed Computing?

- **Understanding of the design space comes at increased computational cost**
  - **Sensitivity analysis - finite difference(2n)**
  - **Design scan - (partial, factorial, DOE) (n^m)**
  - **Response surface (n sampling points)**
  - **Optimization (iterative)**
  - **Taguchi analysis (orthogonal array)**
  - **Probabilistic analysis (Monte Carlo simulation or other)**
  - **Probabilistic sensitivity analysis (variability sensitivity)**
  - **Probabilistic optimization**
- **All involve one to three orders of magnitude more function evaluations than the traditional approach**
- **A design framework with out a robust distributed computing element is not a scaleable practical tool for design shops**

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Figure 13

DISTRIBUTED COMPUTING AND INTERNET TECHNOLOGY

The internet revolution is developing technologies that will make it easier to implement the distributed computing model in engineering design. It is prudent to develop engineering design framework software solutions that leverage the enormous investments and progress made in the computing industry to assemble virtual design teams and collaborative solutions.

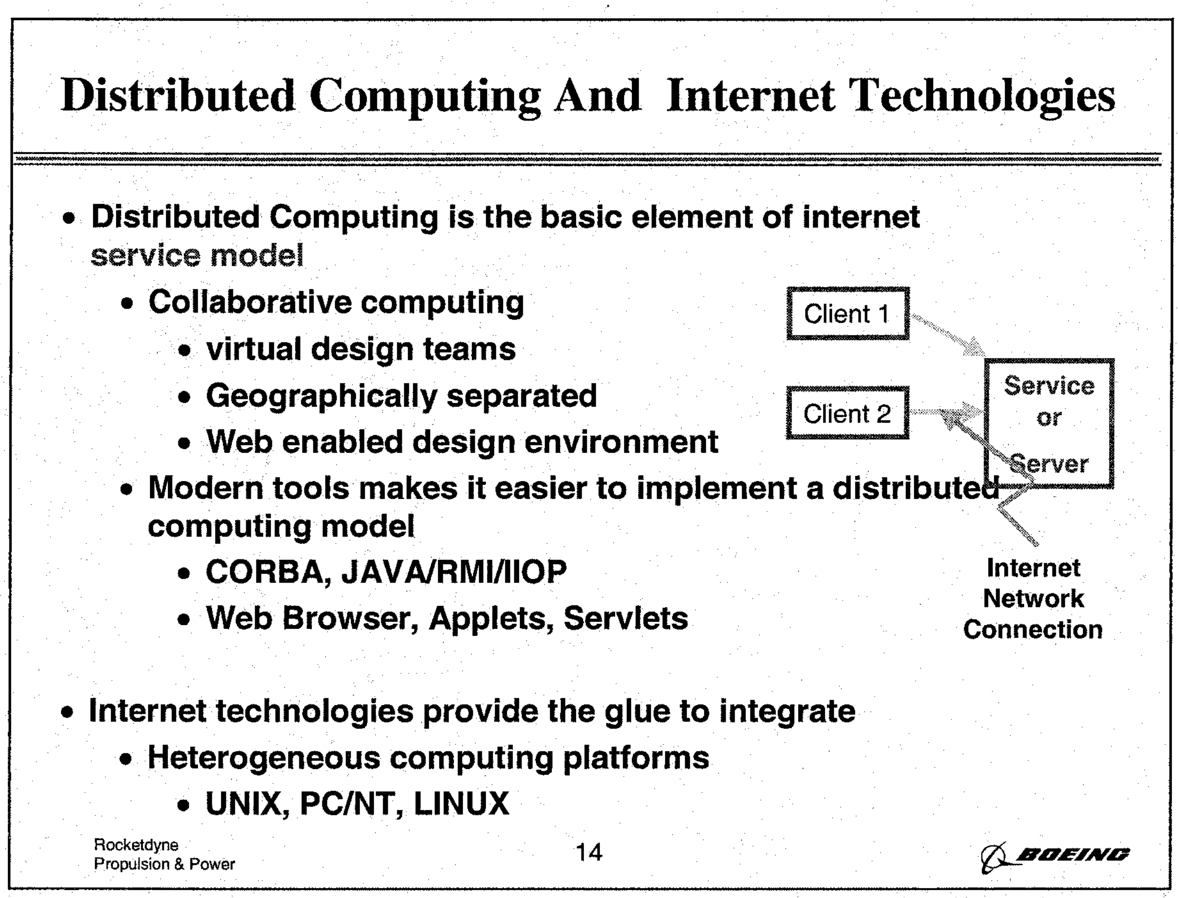


Figure 14

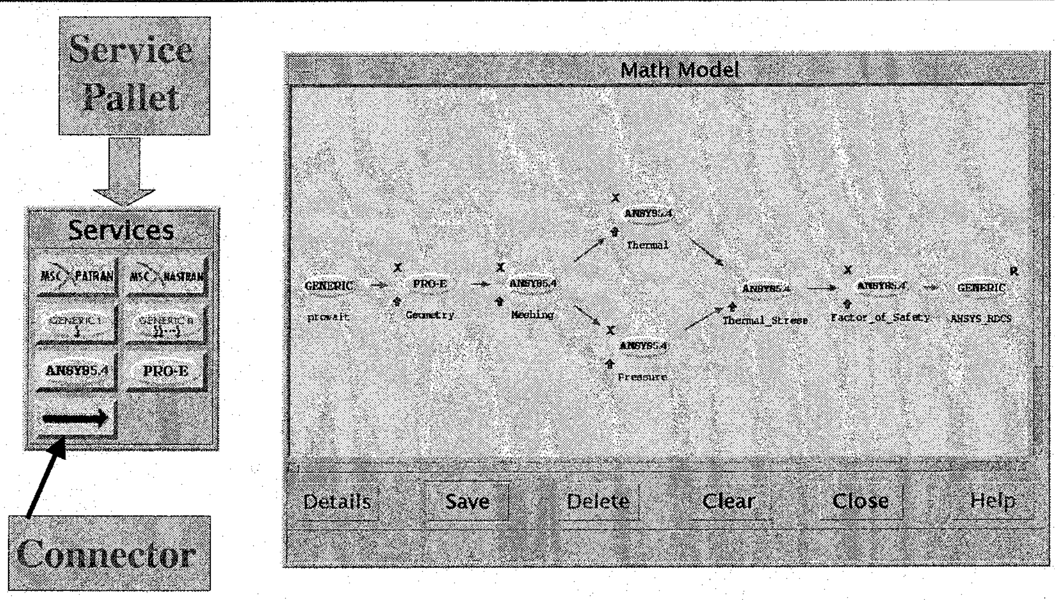
GRAPHICAL MATH MODEL CONSTRUCTION AND DISPLAY

The following slides are actual screen shots from the RDCS system. The left palette represents suite of analysis tools that a typical design shop might use in their design process. The palette is site configurable and the suite of tools can change from one design shop to another.

The user simple clicks the icons in the palette and drops the analysis code in the sketch pad repeatedly to construct a network of codes to be executed in a particular order determined by the arrows. This network of functional models with arrows representing the information flow represents the actual design process used for that component perhaps representing many domains. The live buttons and arrows in the sketch pad can be clicked to provide additional screens completing all the information that is needed to execute the entire sequence.

It is very common to achieve several orders of magnitude improvement in the design cycle time using this automate feature of the RDCS system over conventional manual execution of codes in sequence.

Graphical Math Model Construction and Display



• **Bottoms Up or Top Down Construction**

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Figure 15

The RDCS philosophy is to provide the engineer with information that he is used to as well as provide the more extensive design space exploration results. In this case, the conventional deterministic worst-case analysis provides information that can be used to arrive at safe designs but does not provide detailed information about product performance at other design conditions or at an another point in the design window.

Deterministic Design Concepts

- **Deterministic typical worst case design provides information about margins but frequently more information is needed**

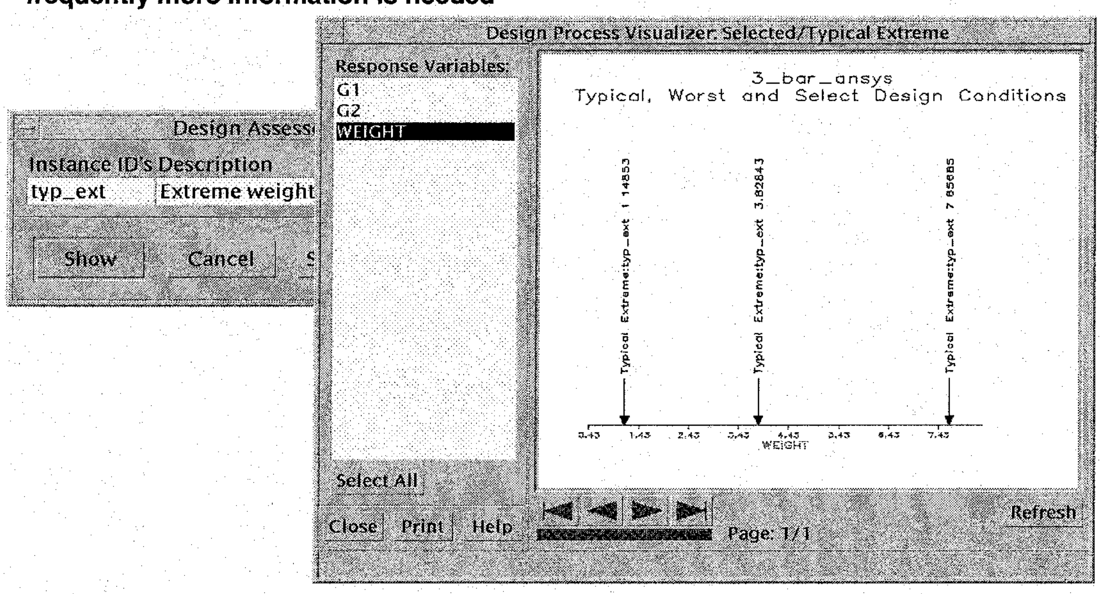

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Figure 16

UNDERSTANDING THE DESIGN SPACE – DESIGN SENSITIVITY PROVIDES VARIABLES RANKING

The deterministic sensitivity analysis provides a way to rank the input variables based on their effect on output performance. This can help the engineer to determine which knob to turn to achieve the desired effect. Typically this is done at a nominal design point. If the behavior is nonlinear it is necessary to perform several sensitivity analysis at different design points.

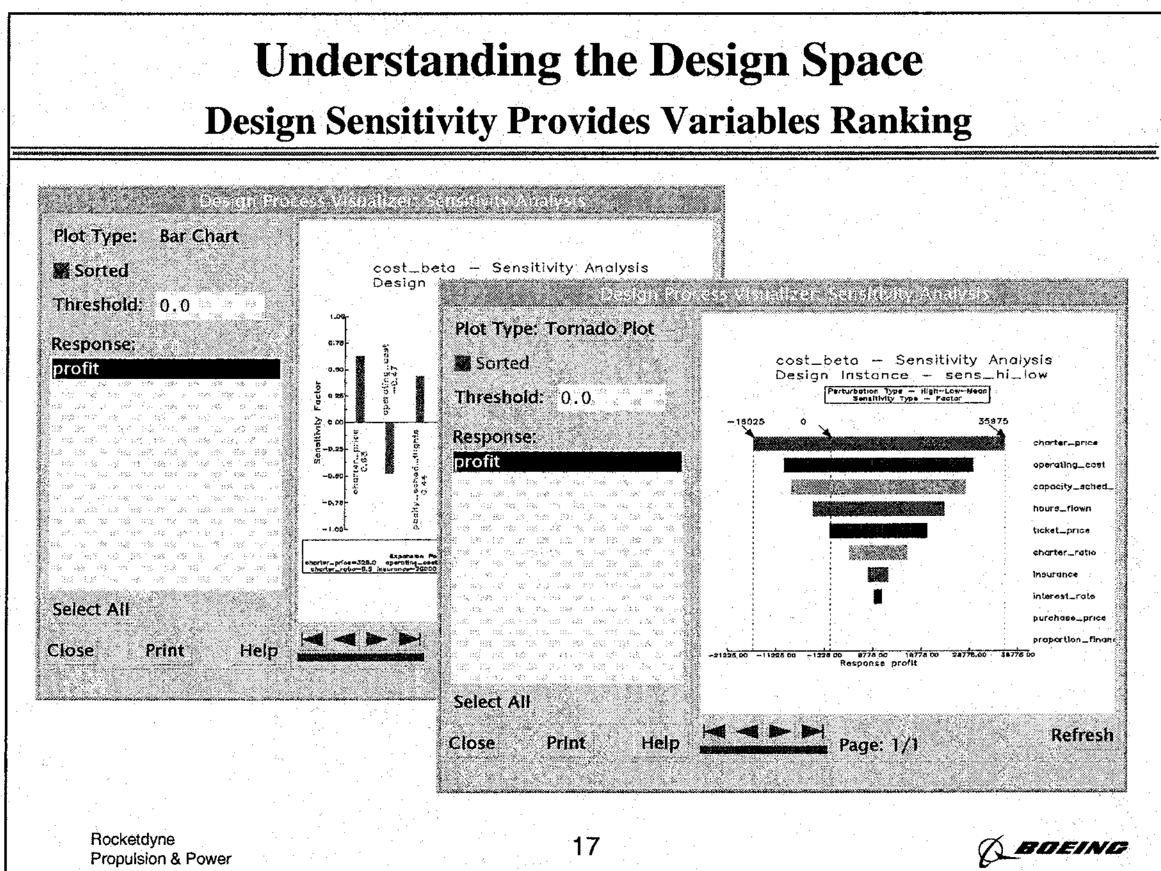

Figure 17

UNDERSTANDING THE DESIGN SPACE
– DESIGN SCAN VIEW OF THE DESIGN SPACE

A detailed design space scan of the effect of input on output over the entire deign window is one of the most powerful feature of the design space exploration. It provides the engineer a comprehensive view of the product behavior over the entire range (from benign linear to highly nonlinear). The use several types of factorial designs and the available computing power to obtain the desired information makes this a practical and often used feature of the RDCS system.

Understanding the Design Space
Design Scan View of the Design Space

- **Several Sampling Schemes Exist - Partial, Full factorial, Design of Experiments**

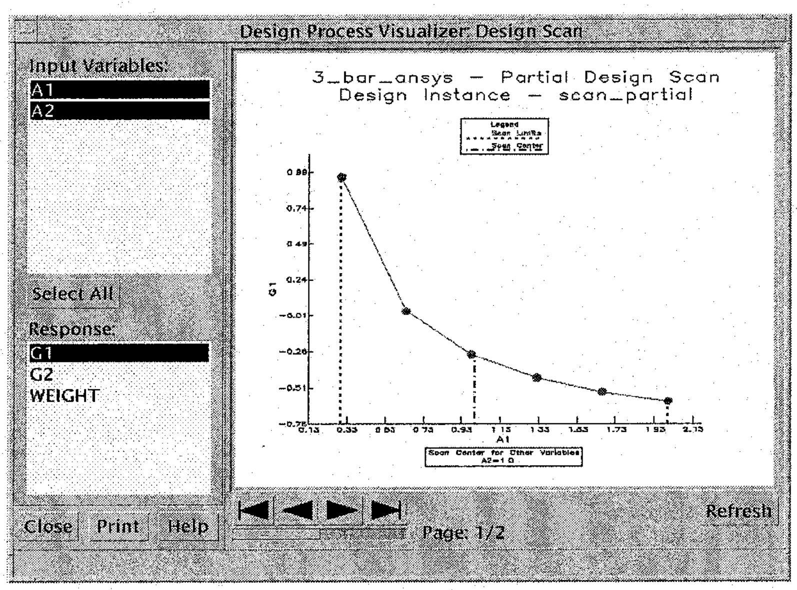

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Figure 18

UNDERSTANDING THE DESIGN SPACE – RESPONSE SURFACE

The response surface generation is a very useful feature of the RDCS system not only to visualize but also to use the response surface as a surrogate model in probabilistic or optimization design processes.

Understanding the Design Space

Response Surface

- **Two Way Design variable Interaction**

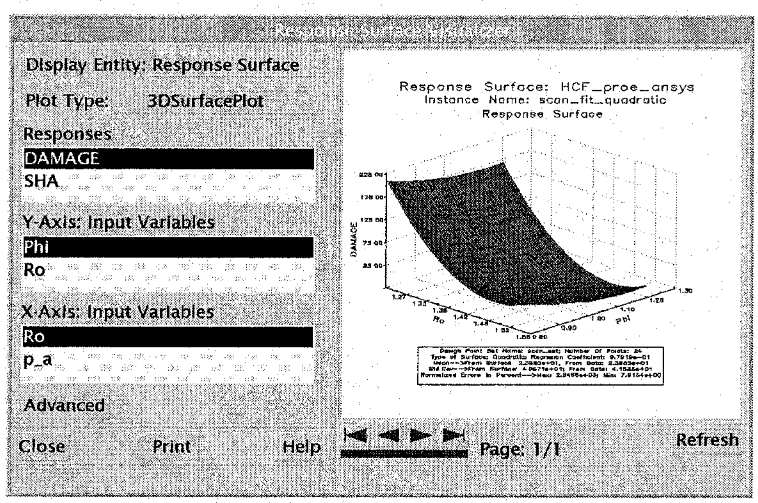

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Figure 19

UNDERSTANDING THE DESIGN SPACE – DETERMINISTIC OPTIMIZATION

The mathematical optimization design process is one of the many tools available in the RDCS system. The key point here is for the engineers to be sensitive to the presence of variations of the design variables and make an assessment of the effect of variations on the objective function.

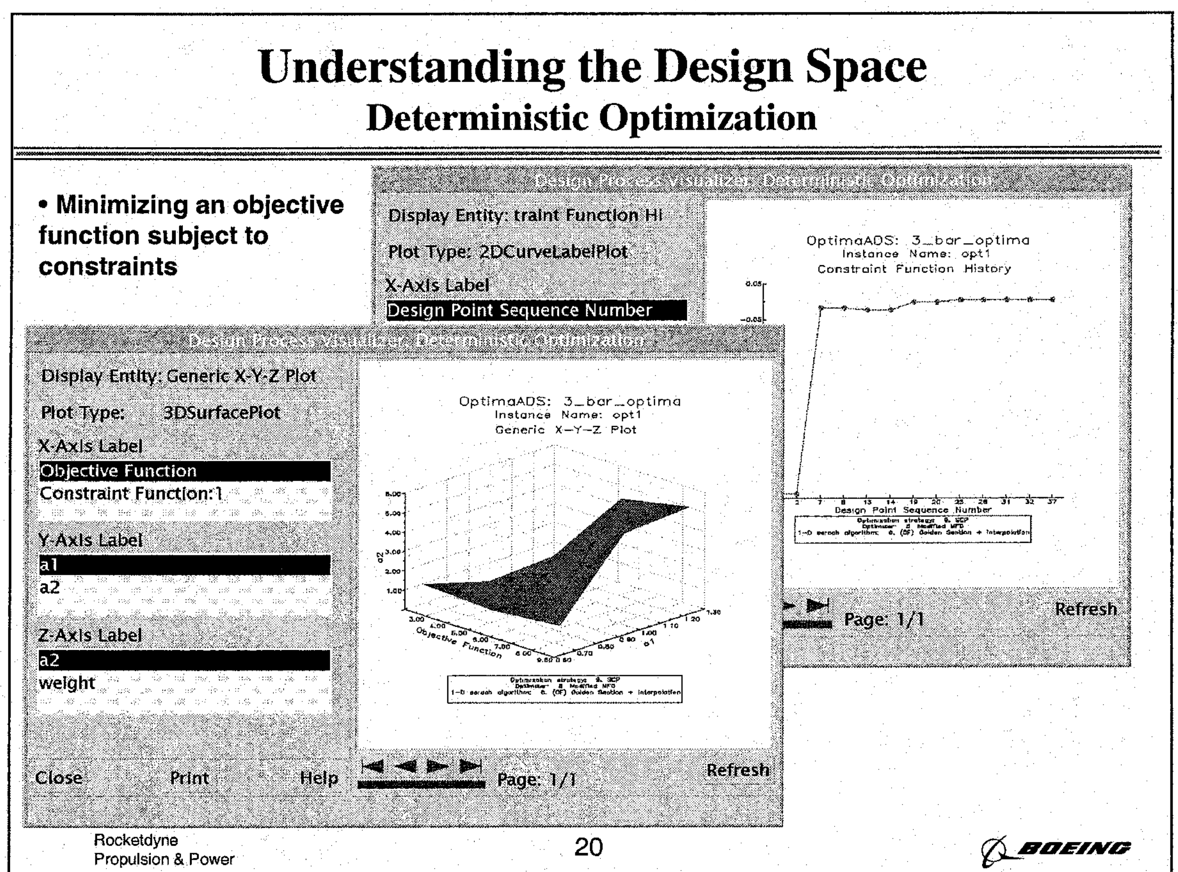


Figure 20

UNDERSTANDING THE DESIGN SPACE – TAGUCHI VIEW OF DESIGN

Taguchi analysis is very popular at the production shop in which the experiments are performed using the actual hardware. In the context of the RDCS system, the experiments are performed on the numerical models, but otherwise the Taguchi process remains the same.

The automatic selection of the orthogonal array based on built-in features inside the RDCS system makes it practical to perform this type of analysis at a product design shop. The design cycle time improvement over the manual methods can be several orders of magnitude.

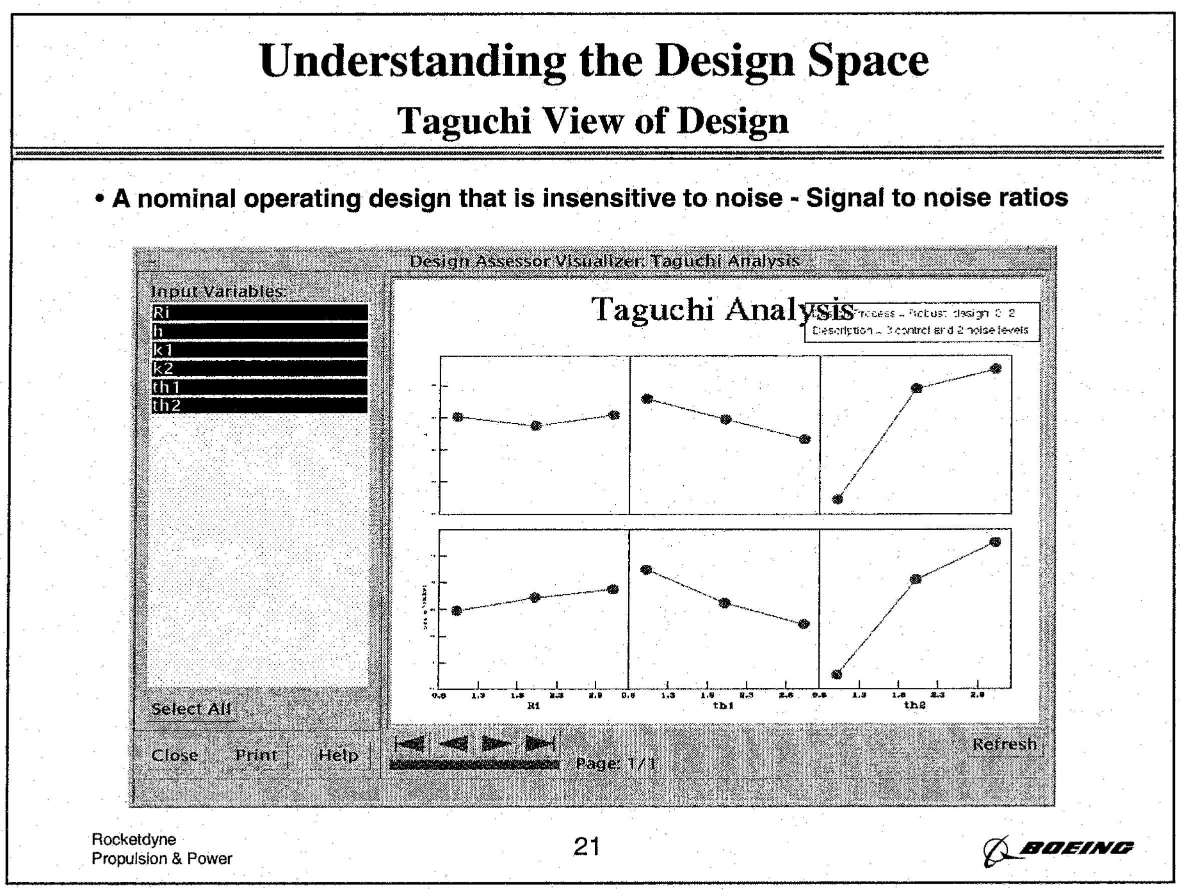
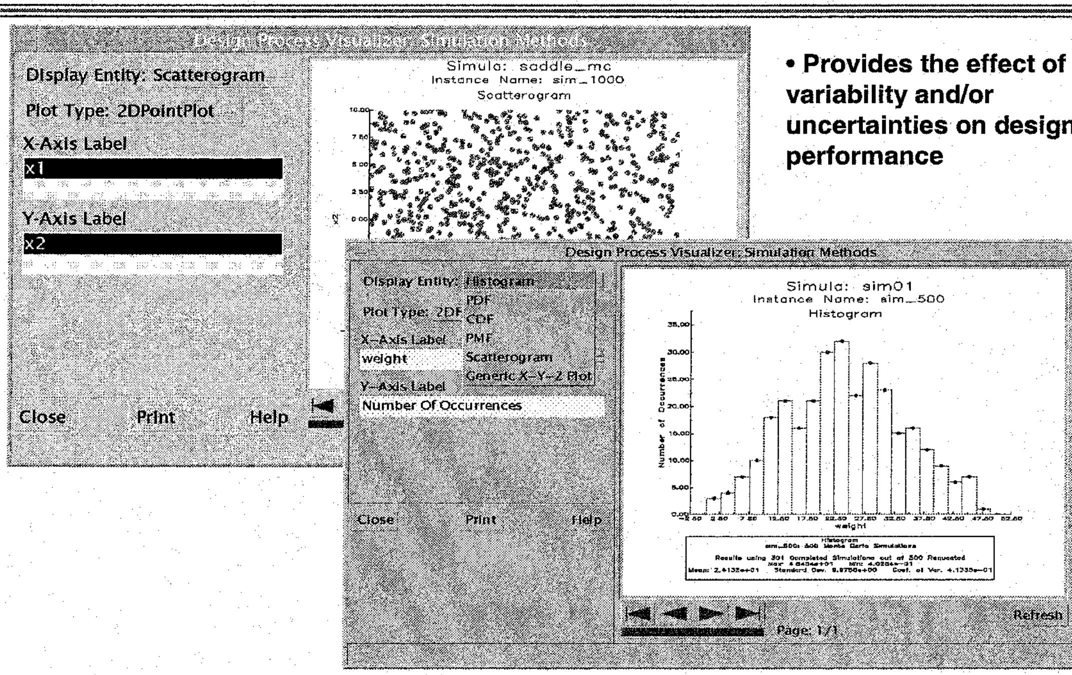


Figure 21

UNDERSTANDING THE DESIGN SPACE – PROBABILISTIC ANALYSIS

Use of the probabilistic analysis will provide quantified reliability estimates. There a variety of distribution models such as Normal, Weibulll, Exponential etc., are available to model the input variations. The output variations can be represented as Probability Density Function, Cumulative Distribution Function as well Frequency Diagrams, Scatter Plots etc.. The key point here is that when probabilistic results are viewed along with extensive design space exploration and other design process views of the product, the engineer gains a comprehensive knowledge of all aspects of expected product behavior.

Understanding the Design Space
Probabilistic Analysis



• Provides the effect of variability and/or uncertainties on design performance

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Figure 22

RDCS APPLICATIONS

The RDCS system has been successfully used in a variety of industries such as automobile industry, space industry as well in airplane industry. The breadth of the applications lends credence to the design framework concept with all the benefits discussed earlier and is in fact filling in a customer demand.

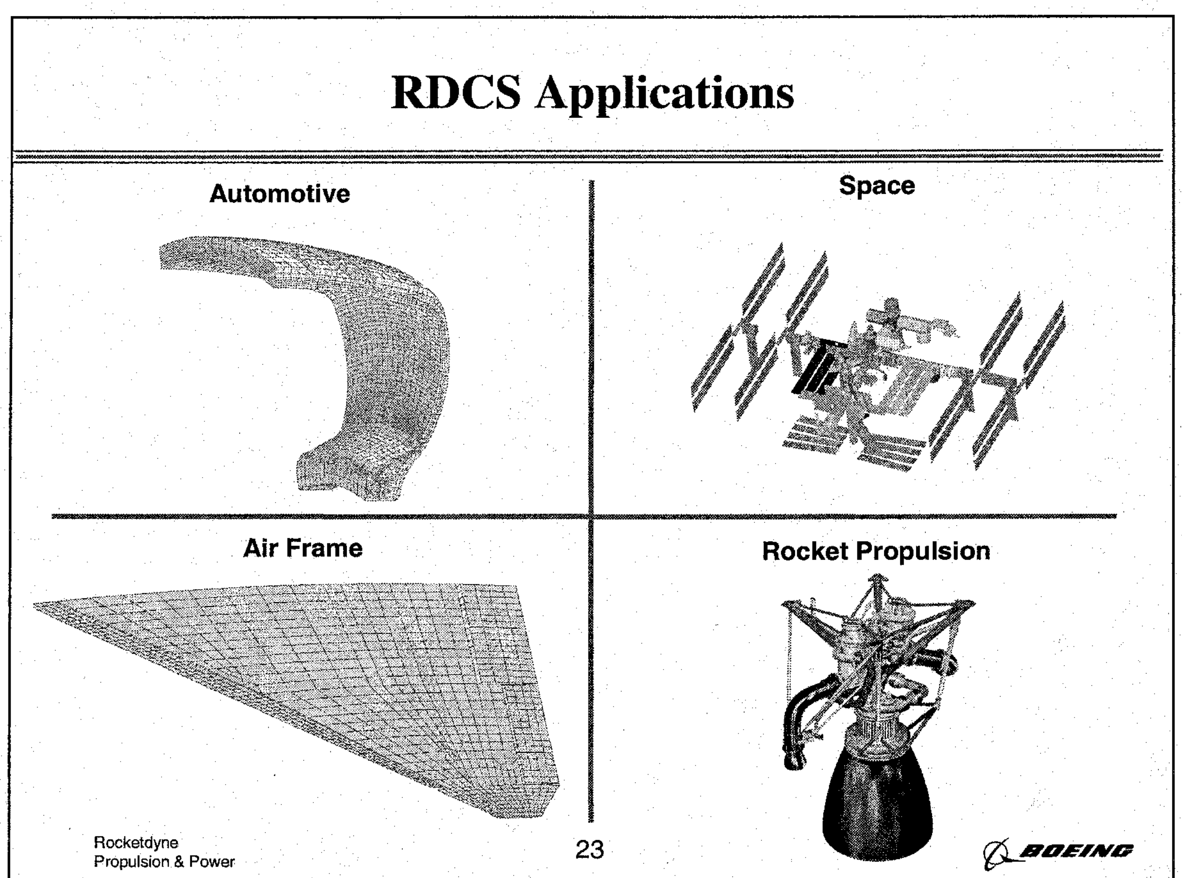

Figure 23

CONCLUDING REMARKS

The challenge is to design and build products meeting cost and schedule constraints effectively. The product should perform as expected the first time. Early indications are that the use of design frame works such as the RDCS system have great potential to meet that need.

Concluding Remarks

- **The concept of design framework is very successful**
  - **Dramatic improvements in multi-disciplinary analysis / design cycle time**
  - **A road map for achieving robust designs**
  - **Cost avoidance because of design space exploration**
  - **Demonstrated the value of introducing the NDA approaches progressively.**
  - **NDA is a critical technology but it is one of the many other technologies to achieve reliable designs**
  - **Use of the tool popular with advanced design groups, but, making significant in-roads in to product teams**

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Figure 24

Overview of Probabilistic Risk Assessment at NASA: Past, Present and Future

Dr. Michael G. Stamatelatos
Office of Safety and Mission Assurance
NASA Headquarter, Code Q
Washington, D.C. 20024

RARE THINGS DO HAPPEN

PRA adds the "probability" dimension to the traditional "deterministic" dimension of engineering and safety analyses. Although PRA, as a discipline, has been the evolutionary product of only the last couple of decades, much of the underlying methodology has been in use for a long time. In fact, the concept of probability for describing the likelihood that rare events happen is ancient and dates from Ancient Greece.

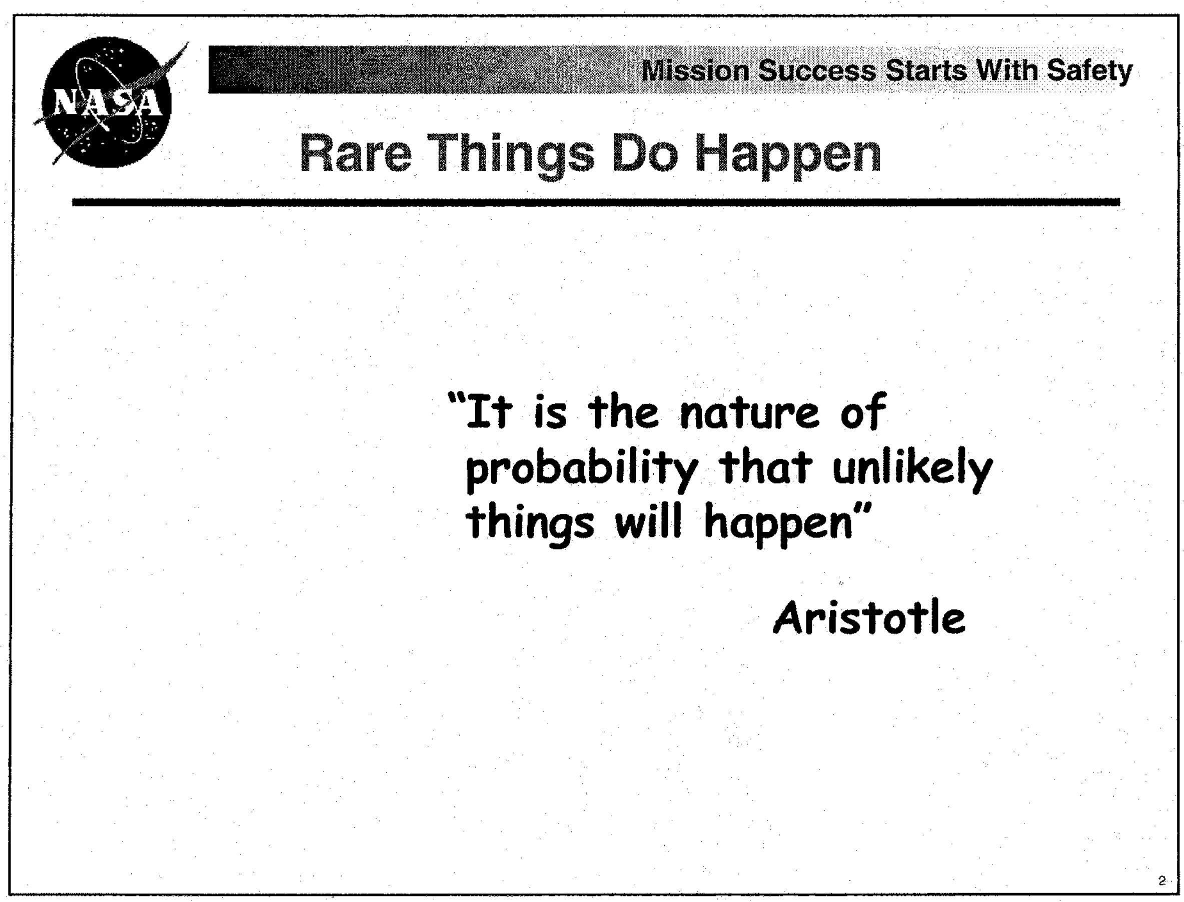

Figure 1

NASA MANAGES RISK ON A DAILY BASIS

NASA is an organization that deals with unique and pioneering technological projects essentially routinely. Therefore, NASA deals with the concept of risk, either explicitly or implicitly, on a daily basis. Also, safety is a top priority at NASA and it is being applied to public, astronauts and pilots, personnel, and property in exactly this order.

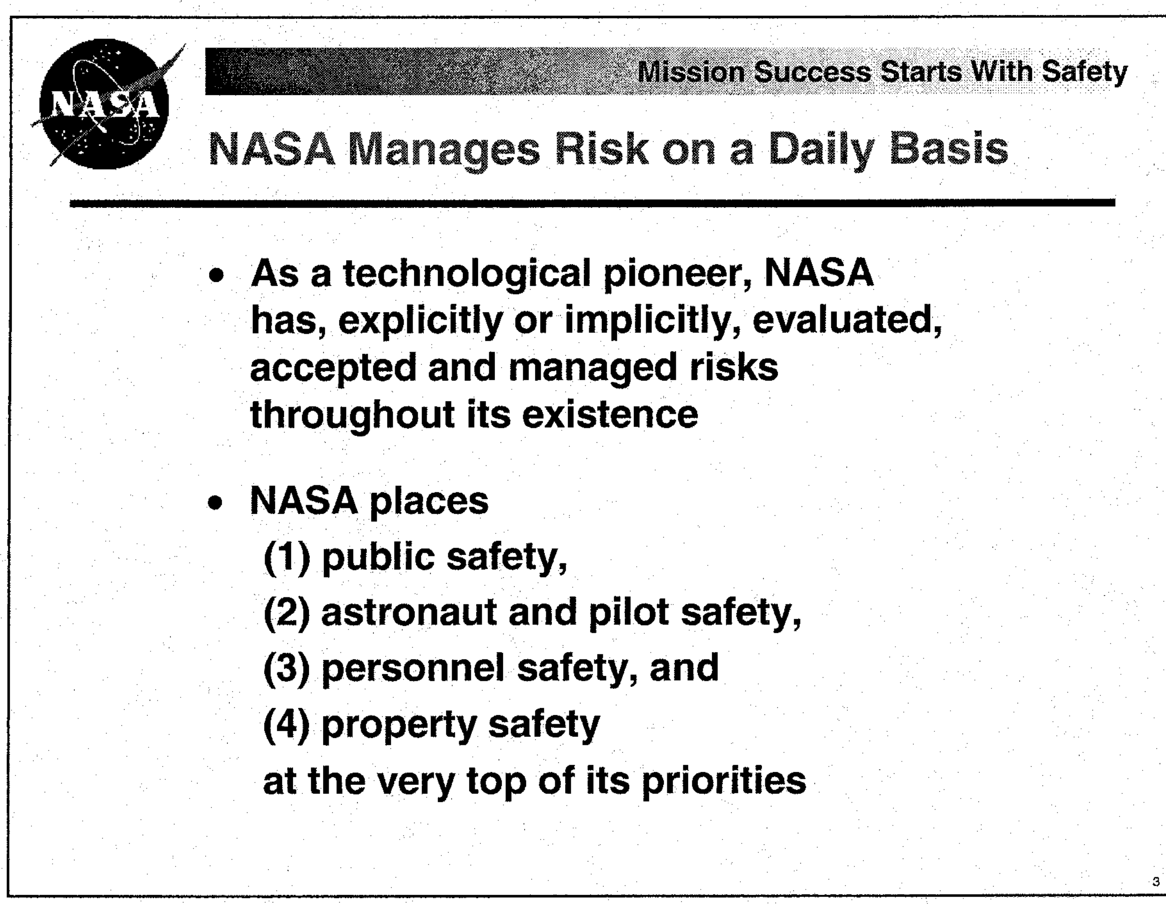

Figure 2

NASA PRA VISION

Our vision is for NASA to achieve world-class state-of-the-art capability in performing and using PRA in technical and management decisions. Since NASA is a leader in many technical fields in which it is involved, we hope, before long, to see NASA become a leader in this field also.

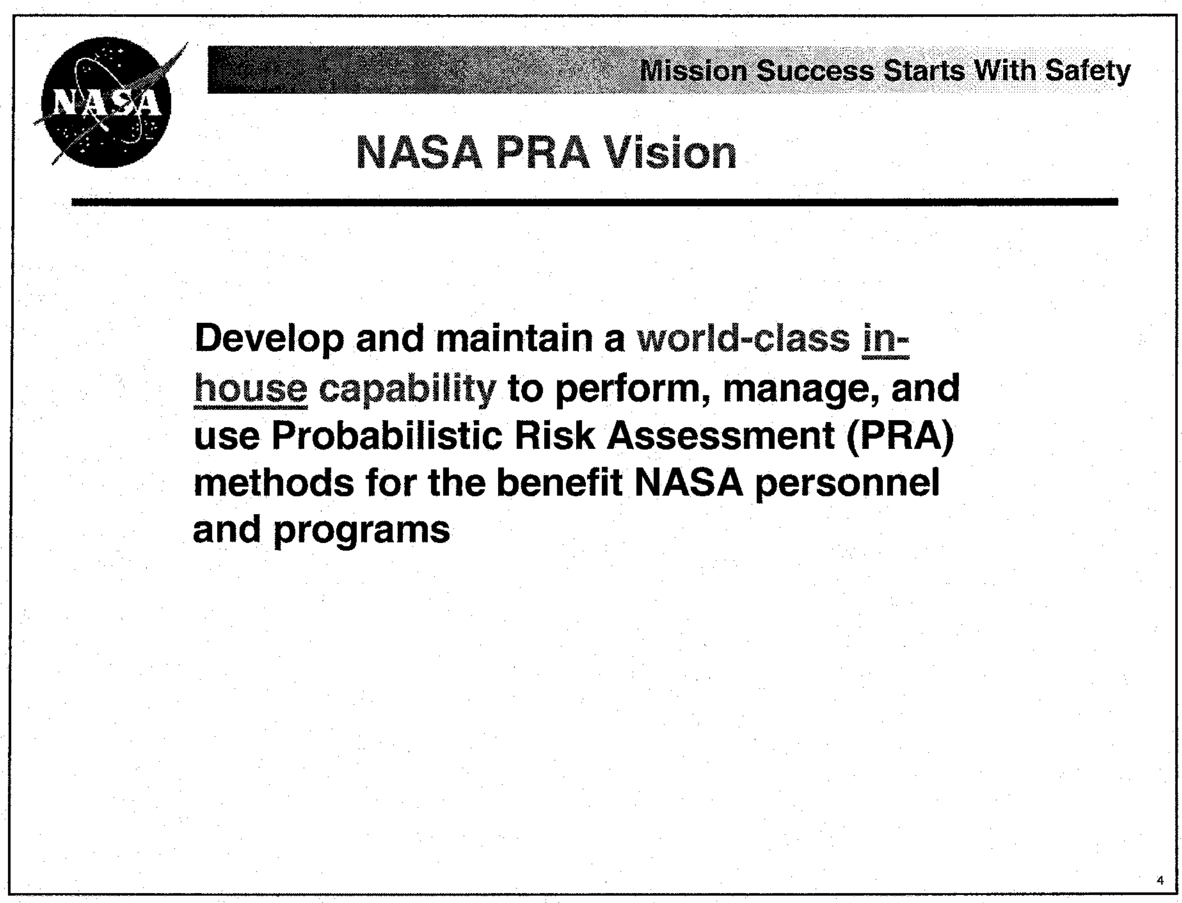

Figure 3

NASA PRA OBJECTIVE

NASA's objective is to develop and use state-of-the-art PRA methodology to help ensure mission success, improve safety throughout product life cycle, improve performance and, eventually, reduce design, operation, and maintenance costs.

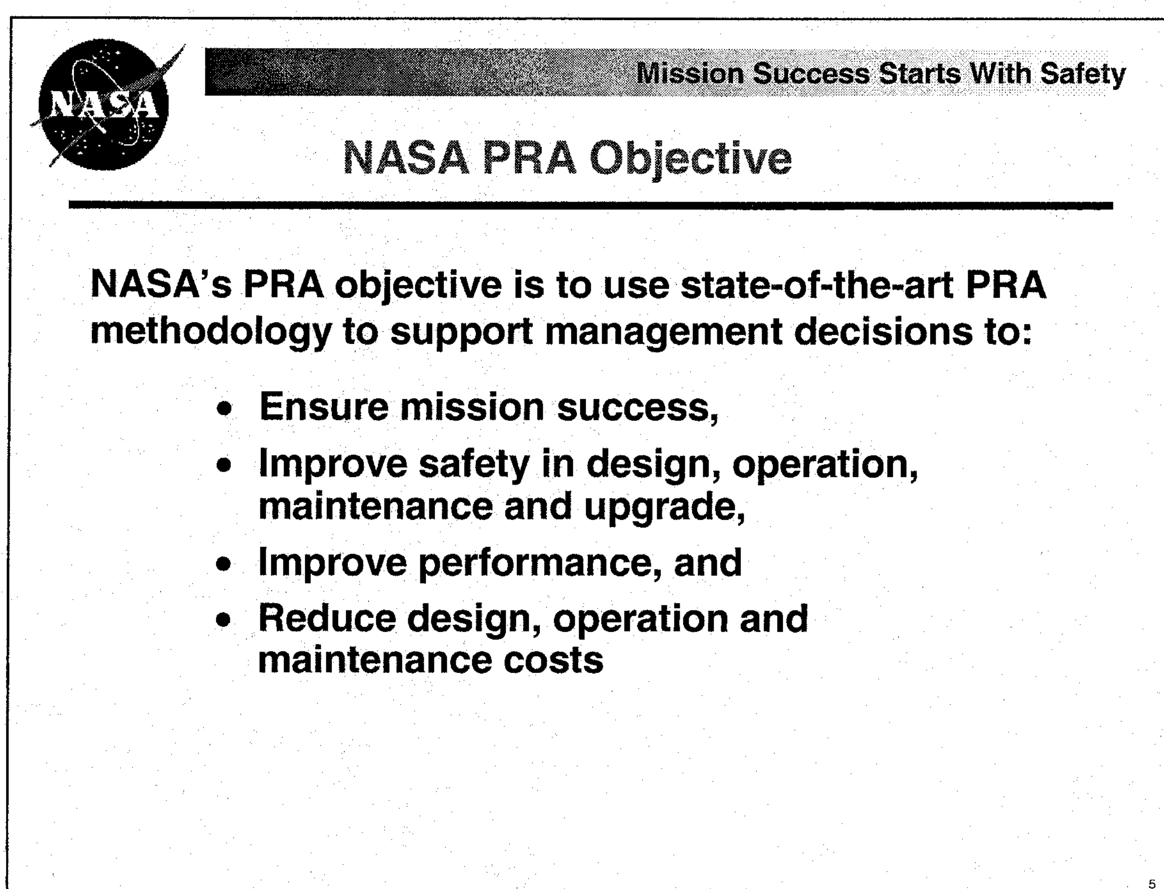

Figure 4

IT WAS NOT ALWAYS THAT WAY...

Some of the important techniques currently used in a PRA (e.g., fault trees) were, in fact, developed some forty years ago in connection with aerospace applications. Early in the Apollo project, a pessimistic probabilistic estimate of mission success, calculated to be 0.2, strongly disappointed NASA managers. Nevertheless, NASA was not deterred by this prediction and, later on, experience showed a much higher probability of success. Thus, the credibility of PRA was lost for many years at NASA who proceeded with the use of only Failure Modes and Effects Analyses (FMEA) in support of their safety assessments. It was not until the Challenger accident and mainly after recommendations from outside experts that NASA started again to perform PRAs.

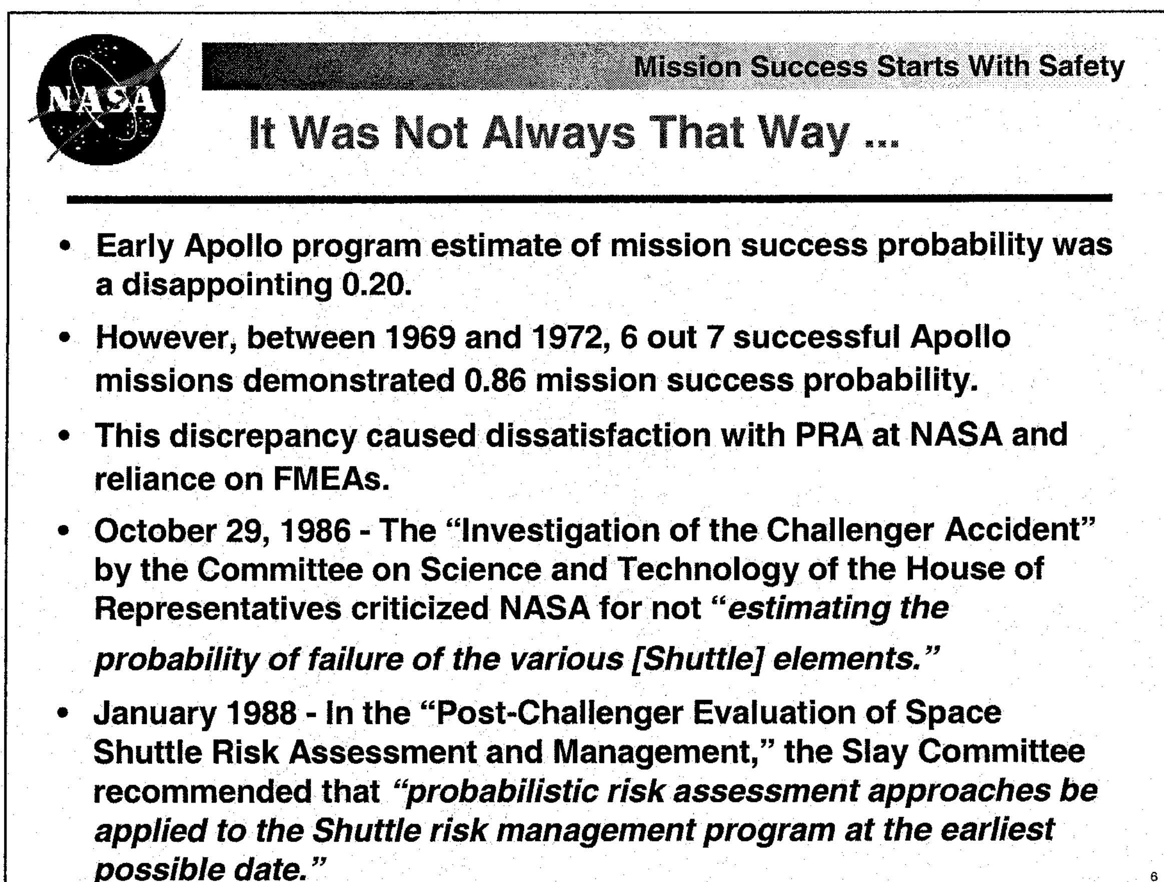

Figure 5

PRA RENAISSANCE AT NASA

Between 1987 and 1995 consultants by NASA performed some fifteen probabilistic studies. Also, the Administrator encouraged the initiation and development of an integrated computerized PRA tool, QRAS. In spite of these initiatives, the use and credibility of PRA at NASA did not grow significantly because some important ingredients were still missing.

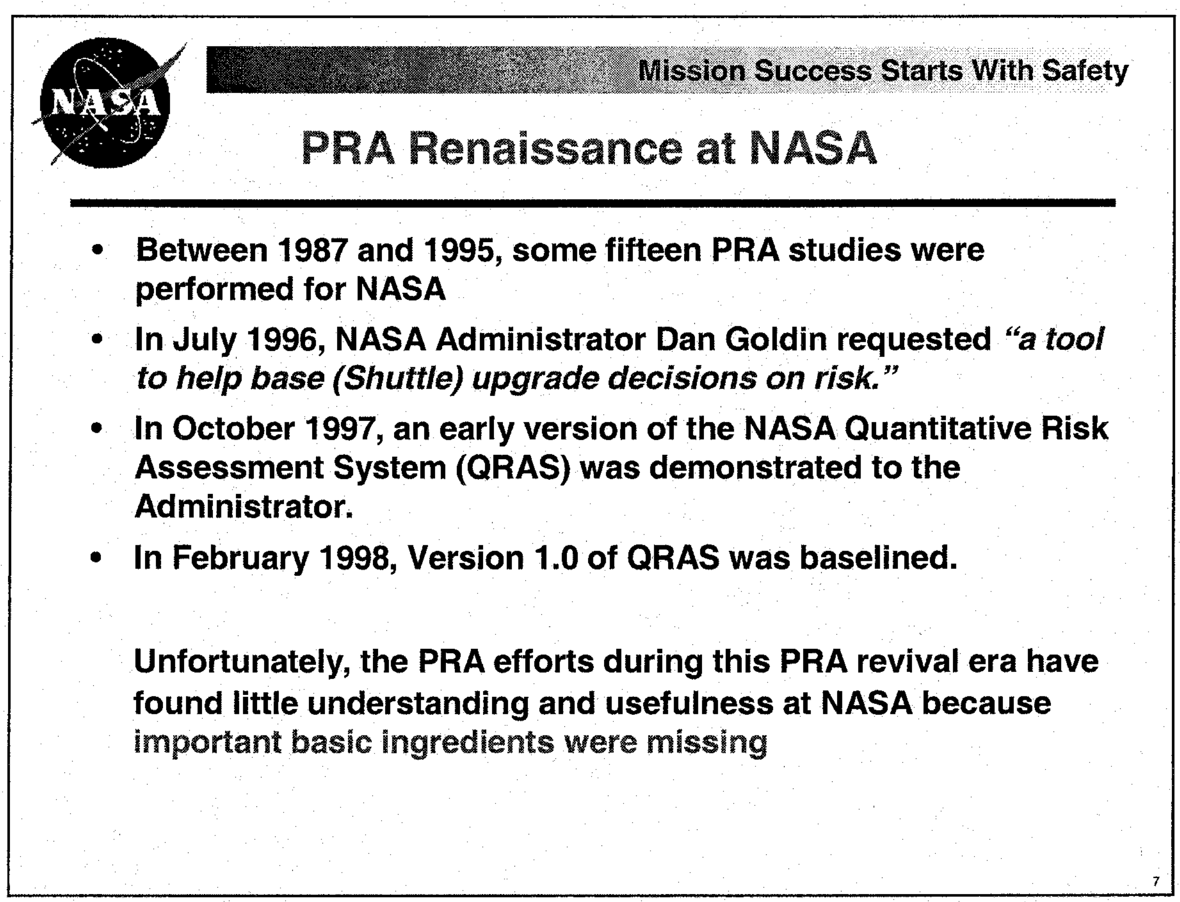

Figure 6

ACQUIRING PROVEN INGREDIENTS FOR SUCCESS

Applications of PRA in other industries, notably nuclear, have shown that optimal understanding, appreciation, and use of PRA techniques are not realized by an organization until in-house personnel of this organization gain important achievements: sufficient in-house expertise to manage and use PRA for management decisions; in-house ownership and corporate memory of PRA methods, computer tools, data, and results; and transfer of PRA technology to the in-house decision makers who use PRA and its results. NASA is aggressively pursuing approaches to reach these achievements.

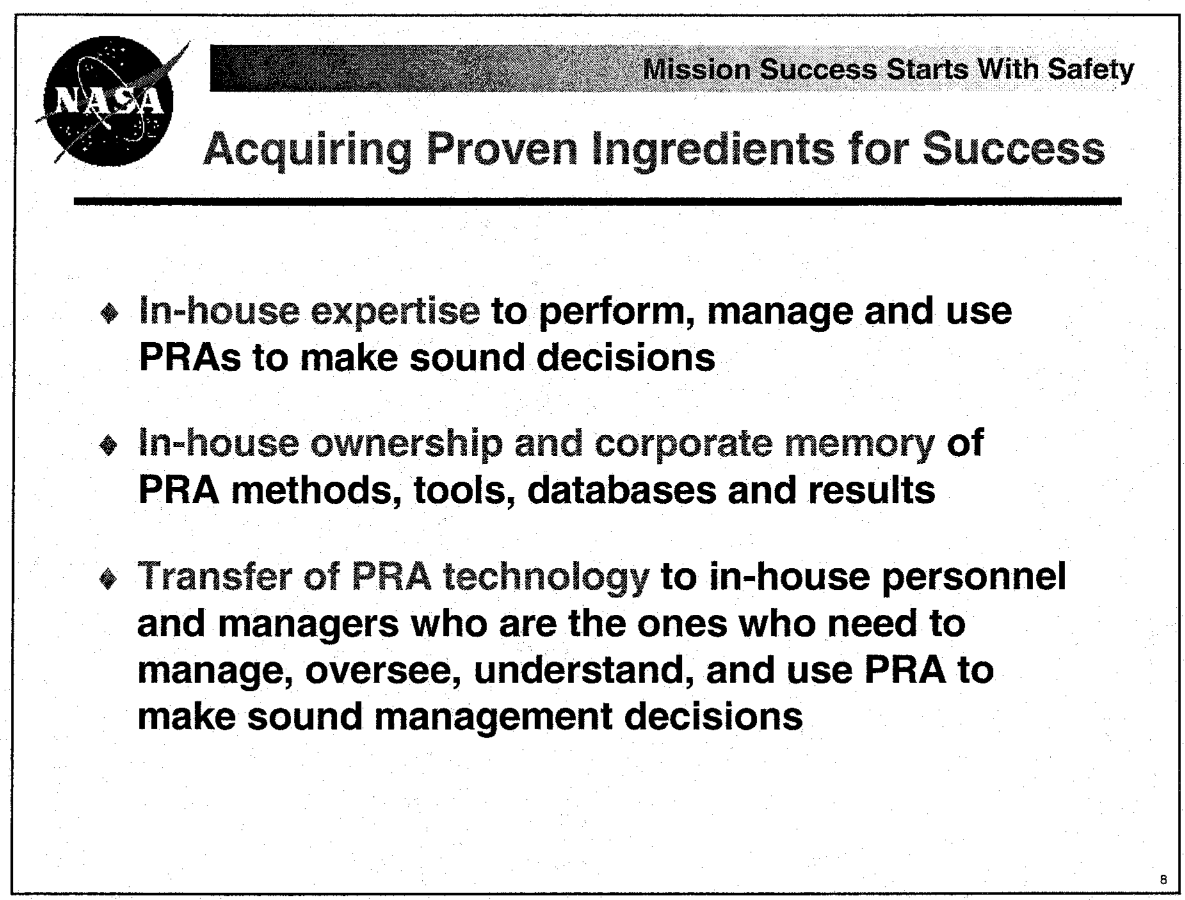

Figure 7

RELATIONSHIP BETWEEN RISK MANAGEMENT AND PRA

Risk of interest at NASA is both of a technical nature and of a programmatic nature, the latter being related to program costs and schedule. Risk assessment covers of the first two elements of risk management: risk identification and risk analysis. Risk assessment can be performed either qualitatively or quantitatively. Techniques like failure modes and effects analysis (FMEA), fault tree analysis (FTA), master logic diagrams (MLD), event sequence diagrams (ESD), and event tree analysis (ETA) can be used in both qualitative and quantitative risk assessments. Additionally, statistical and actuarial techniques, as well as simulation techniques, can be used in quantitative risk assessments. Risk assessment results, in conjunction with decision analysis techniques, are used to formulate risk prevention and mitigation plans. The last two elements of risk management, risk tracking and risk control must be consistent with the organization management system.

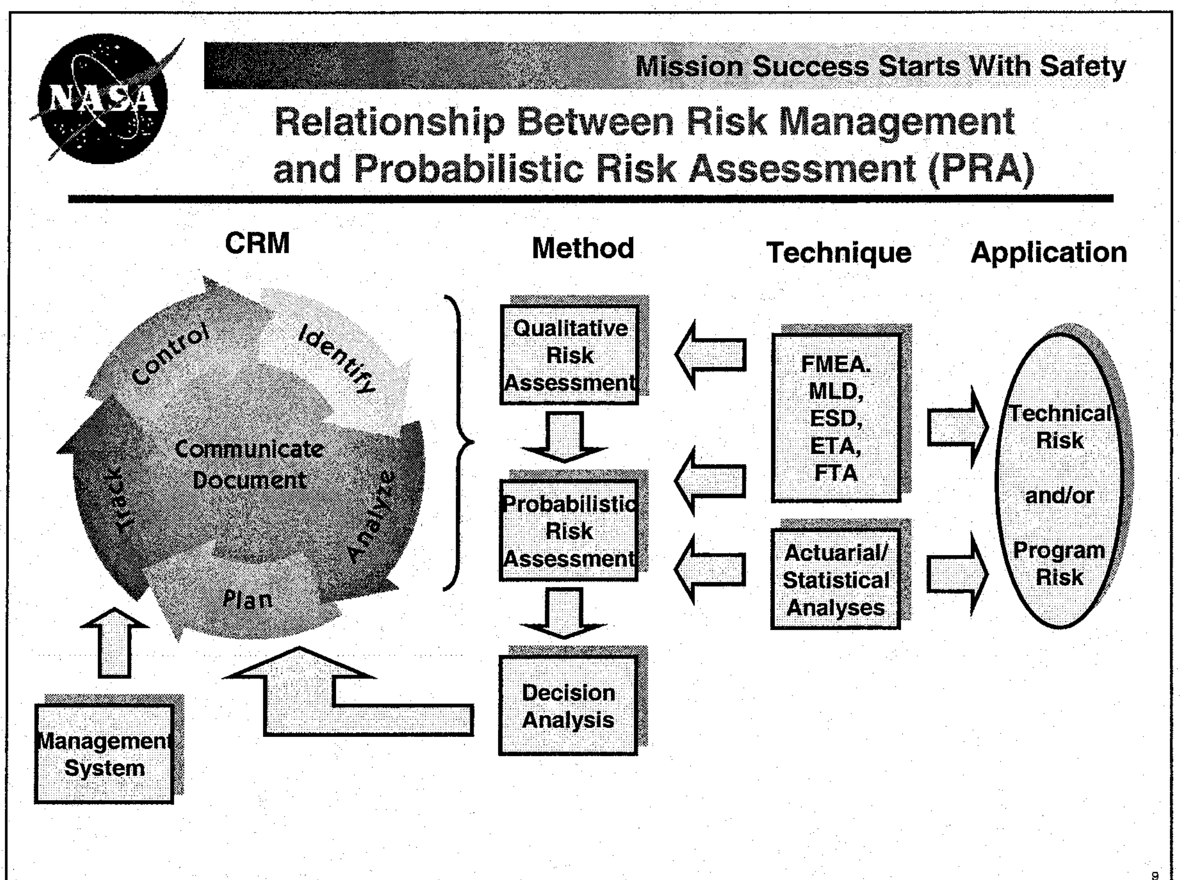

Figure 8

ONE-YEAR ACCOMPLISHMENTS

Within the past year, NASA has made great progress toward reaching its PRA objectives: (1) a policy for PRA use was drafted and is being circulated for comments; (2) a practitioner's PRA procedures guide for aerospace applications was drafted; (3) PRA training at NASA was conducted several times at both awareness level and practitioner's level; (4) more than 90 NASA people were trained on SAPHIRE, chosen by NASA as its "baseline" integrated PRA program which, together with NASA's own program, QRAS, will be used for PRA training and PRA projects; (5) PRA information exchanges have been organized in the form of workshops where NASA personnel can share PRA information and experience; (6) NASA is cooperating in the field of PRA with US organizations that are experienced in PRA, like the Nuclear Regulatory Commission (NRC), and with foreign aerospace agencies, e.g., the European Space Agency (ESA) and the Japanese space agency, NASDA.

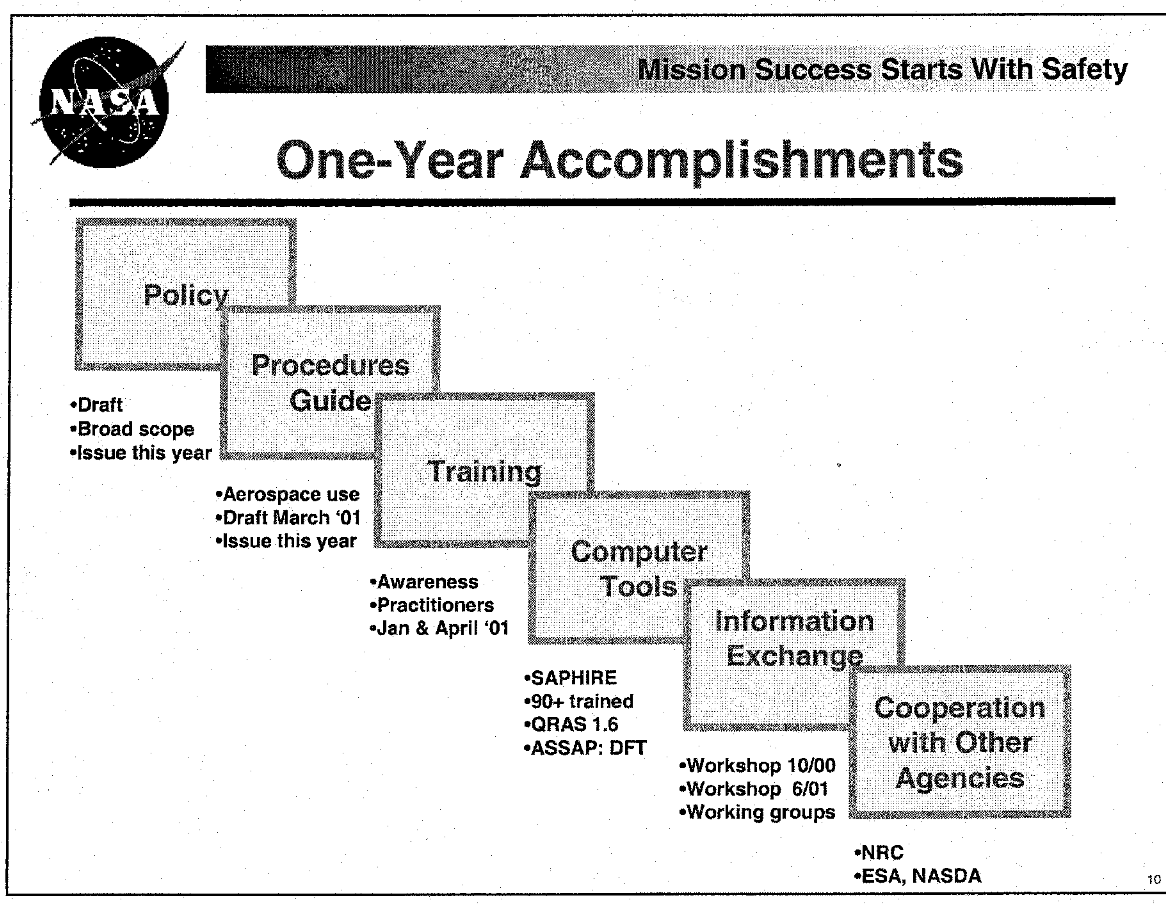

Figure 9

PRA POLICY REQUIREMENTS

NASA is performing PRA for a wide range of programs/projects ranging in nature and detail from conceptual to detailed design, operation and/or system upgrade. Some projects involve human participation while others do not. When the public may be affected, NASA and federal requirements make it necessary to conduct a full-scope PRA. NASA is also performing full-scope PRAs for all human space flights. For non-human rated space projects, the PRA requirements are somewhat different. For programs of high strategic importance, high schedule criticality, or high cost a full-scope, PRA is also required, sometimes at a reduced scope if appropriate. Although PRA is recommended for all projects, only a limited level PRA may be required for lower cost programs and perhaps none for very low cost projects that are not human rated.

Mission Success Starts With Safety

PRA Policy Requirements

CONSEQUENCE CATEGORY	CRITERIA / SPECIFICS		NASA PROGRAM/PROJECT (Classes and/or Examples)	PRA SCOPE*
Human Safety & Health	Public Safety	Planetary Protection Program Requirement	Mars Sample Return	F
		White House Approval (PD/NSC-25)	Nuclear payload (e.g., Cassini, Ulysses, Galileo)	F
	Human Space Flight		International Space Station	F
			Space Shuttle	F
			Crew Return Vehicle	F
Mission Success (for non-human rated missions)	High Strategic Importance		Mars Program	F
	High Schedule Criticality		Launch window (e.g., planetary missions)	F
	Higher-Cost Missions (>$100M)		Earth Science Missions (e.g., EOS)	L
			Space Science Missions (e.g., SIM)	L
			Technology Demonstration and Validation (e.g., EO-1)	L
	Lower-Cost Missions (<$100M)		Earth Science Missions (e.g., QUICKSCAT)	L or N
			Space Science Missions (e.g., HESSI)	L or N
			Technology Demonstration and Validation (e.g., Deep Space 1)	L or N

(*) LEGEND: F = Full Scope; L = Limited Scope; N= None

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Figure 10

QUANTITATIVE RISK ASSESSMENT SYSTEM (QRAS)

QRAS is a NASA integrated PRA computer program that is in many ways similar to SAPHIRE and in some ways different. Like SAPHIRE, QRAS uses event trees and fault trees to model and quantify accident scenarios. Like SAPHIRE, QRAS has the capability to perform dependent failure (also known as "common-cause failure") analysis and uncertainty analysis. Unlike SAPHIRE, QRAS leads the analyst through the development of a hierarchy for hardware systems, sub-systems and components that facilitates identification of hardware failure modes as accident sequence initiators. Unlike SAPHIRE, the scenarios in QRAS are fist developed into event sequence diagrams (ESD), which tend to be easier to understand and develop by system engineers who are not experts in PRA. These ESDs are then transformed into equivalent event trees by the software, without analyst intervention, before the sequence is quantified. Version 1.6 of QRAS was recently released and is now in beta testing. Thus, NASA is in the enviable position of having two state-of-the-art integrated PRA computer programs instead of one.

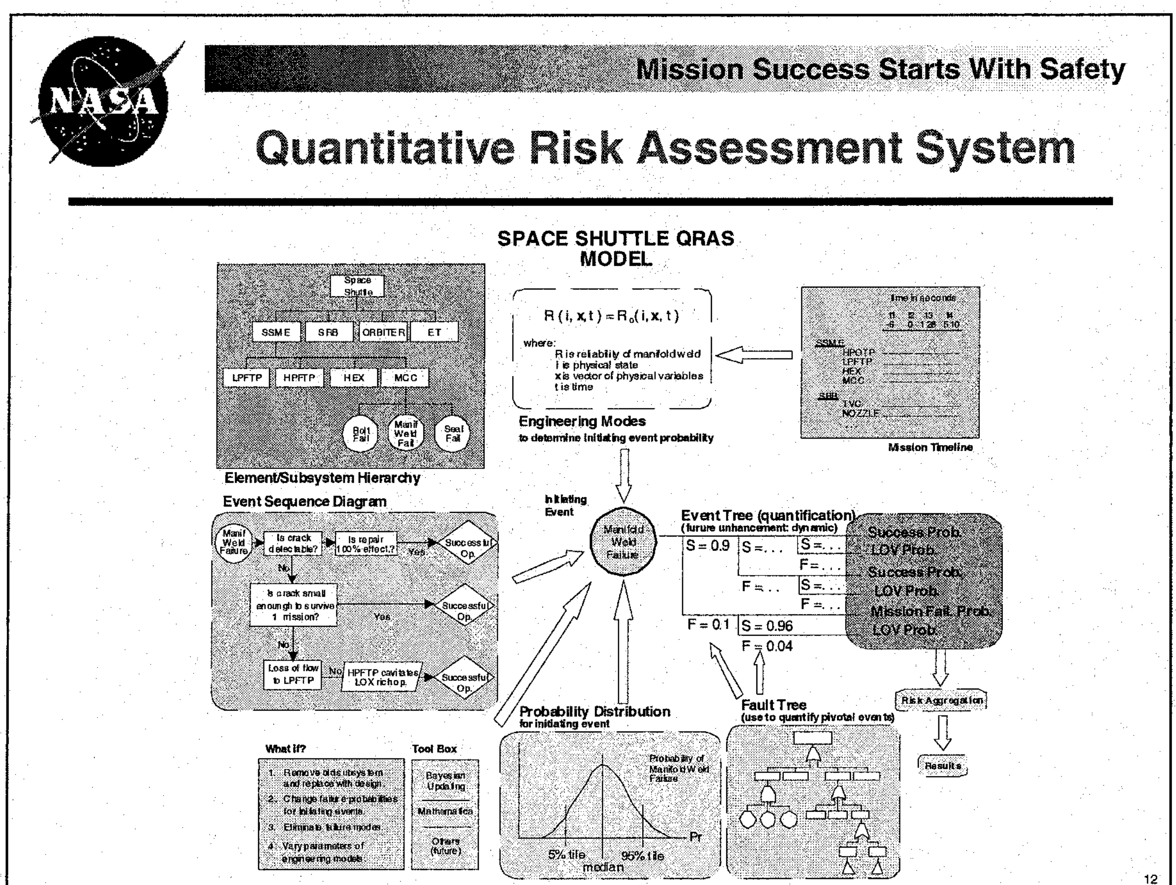


Figure 11

TYPES OF RISK AND RELATED CONSEQUENCES

Risk assessments may be performed for a variety of reasons and associated consequences. These include: safety, environmental impact, cost risk, programmatic risk, mission success, etc. Risk assessments for these different types of applications are generally different in scope and may require the use of different types of techniques for modeling and quantification.

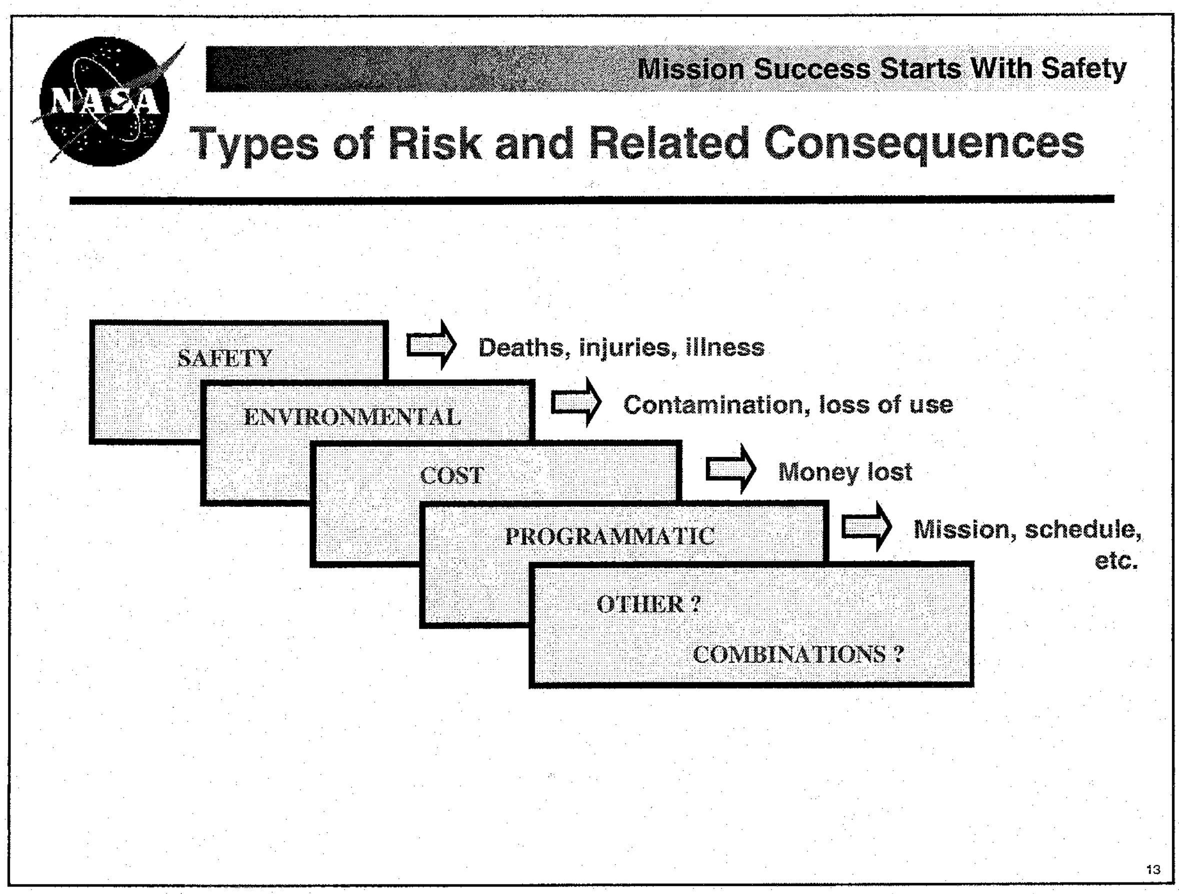


Figure 12

PRA SIMPLY DESCRIBED

A PRA generally provides the answers to three types of questions: (1) what can go wrong? (i.e., what are the scenario initiators?) (2) how frequently does this happen? (i.e., what are the scenario probabilities or frequencies?) and (3) what are the consequences if something goes wrong? (i.e., what is the scenario consequences severity?) The final product is a description and interpretation of the risks being assessed including their numerical values and uncertainties if the assessment is quantitative.

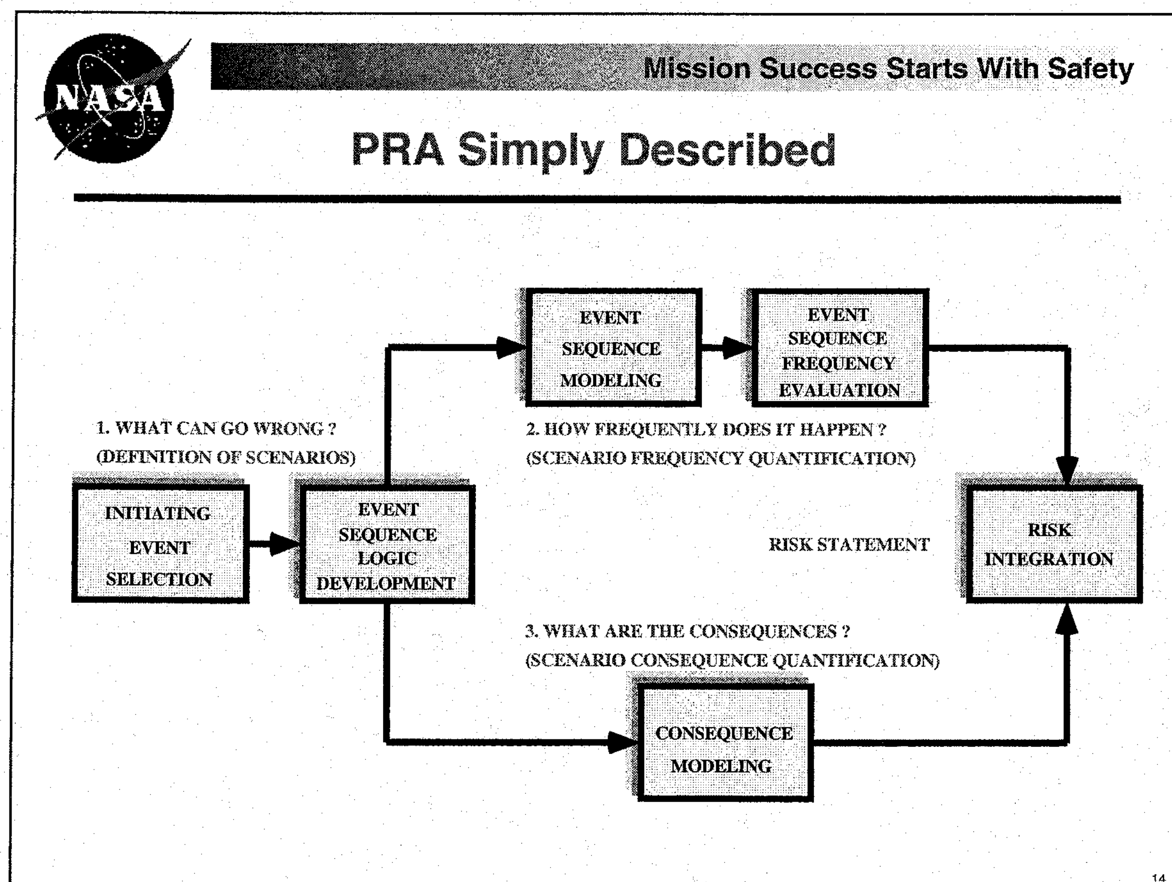


Figure 13

EXPECTATIONS FROM A PRA

The expectations from a PRA are generally assistance in: preventing or mitigating mishaps, mission success or performance enhancement, safety improvements and/or design, operation, and maintenance cost reductions.

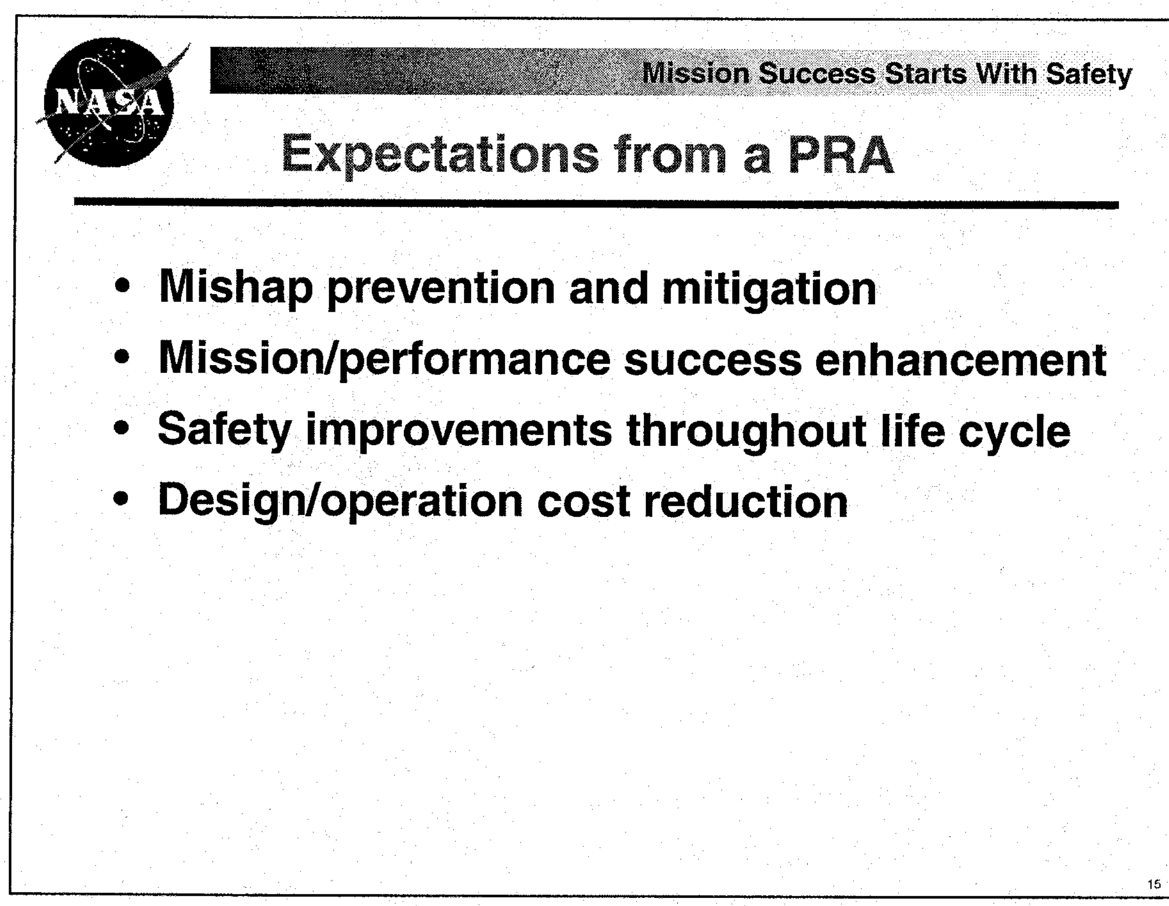


Figure 14

SCENARIO-BASED PRA MODELING APPROACH

The scenario-based PRA modeling approach for safety applications can be diagrammatically shown to consist of: technical or programmatic information collection and analysis; identification of initiators with techniques like the master logic diagram; event sequence development; system failure assessment using fault trees; and evaluation and analysis of the results.

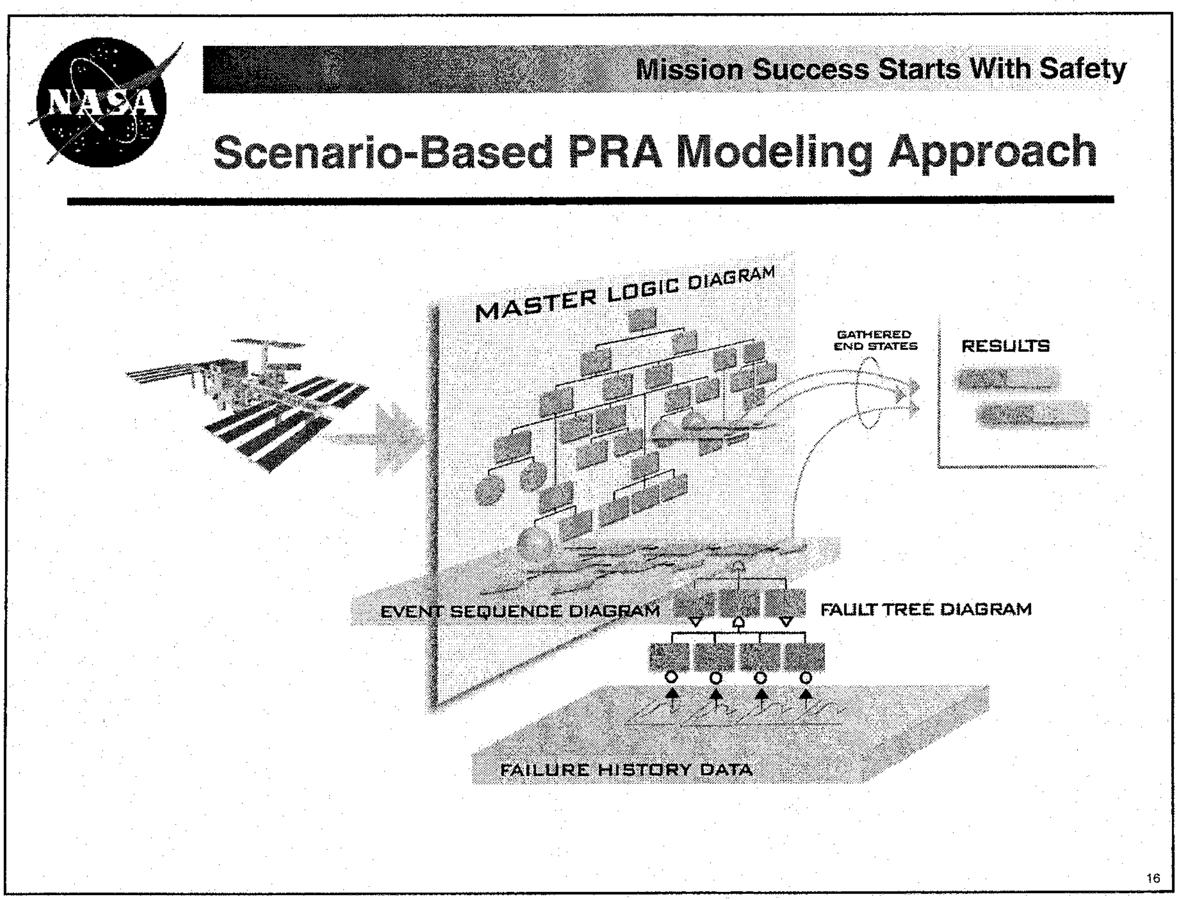


Figure 15

ELEMENTS OF SCENARIO-BASED PRA

The quantitative scenario-based PRA starts with objective definition and proceeds through the following general steps: system familiarization; initiating events identification and selection; scenario, or event-sequence modeling (e.g., using ESD or ETA); failure modeling (e.g., using FTA), quantification and integration of the scenario risks; uncertainty analysis; and interpretation of results. Scattered throughout the PRA process is data collection and processing as necessary. Depending of the analysis requirements, sensitivity analyses and/or importance ranking analyses are also performed.

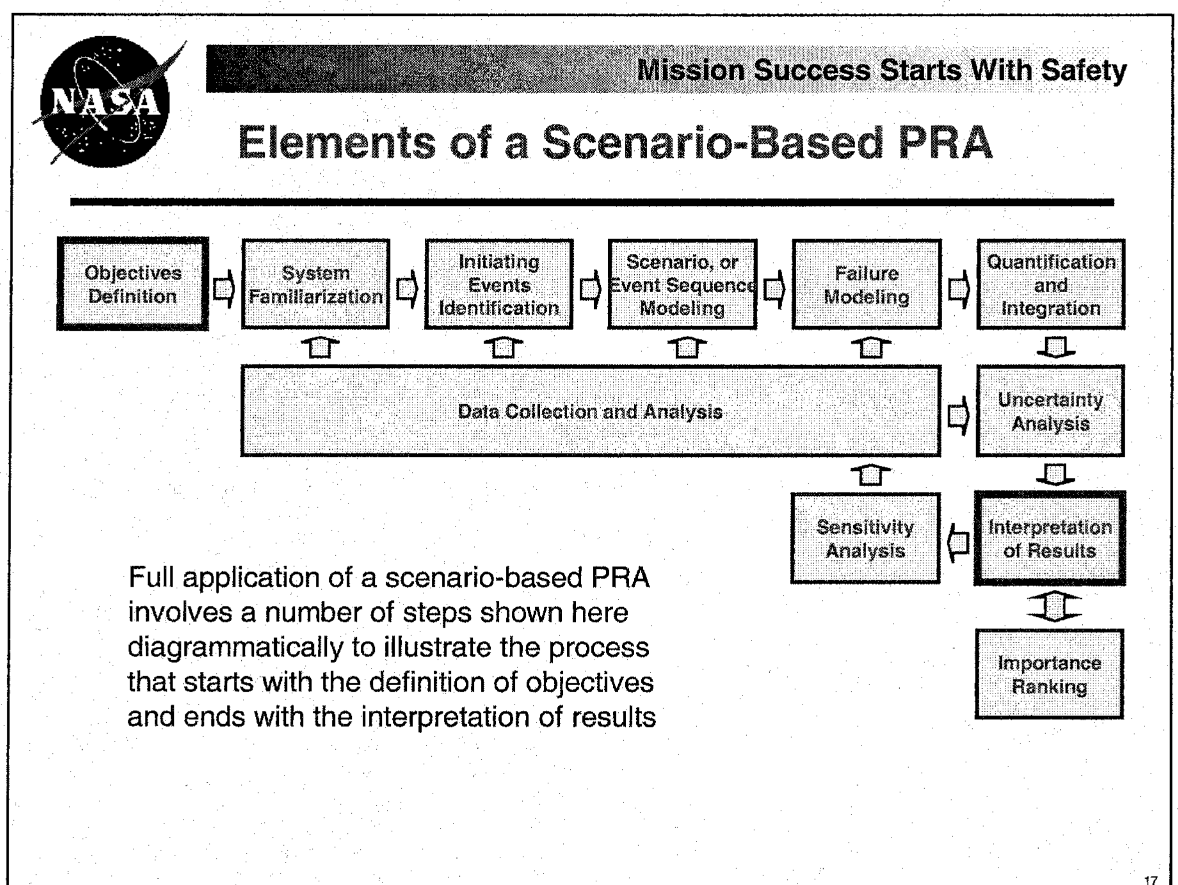


Figure 16

RISK SOURCES IN SAFETY RISK ASSESSMENT

In a safety risk assessment, the risk contributors can be either, all or combinations of the following types of sources: hardware failures, "external" events or acts of nature, human error, or errors due to organizational structures or practices which are globally called "organizational factors." These risk sources are listed here in order of increasing modeling complexity and of decreasing maturity and accuracy in the methodology, modeling and associated data quantity and quality that are generally available to perform risk assessments. Not listed in this diagram, but also very important for NASA applications, are software failures that are currently not being modeled very well because of general lack of data and of sophistication in the analysis methods.

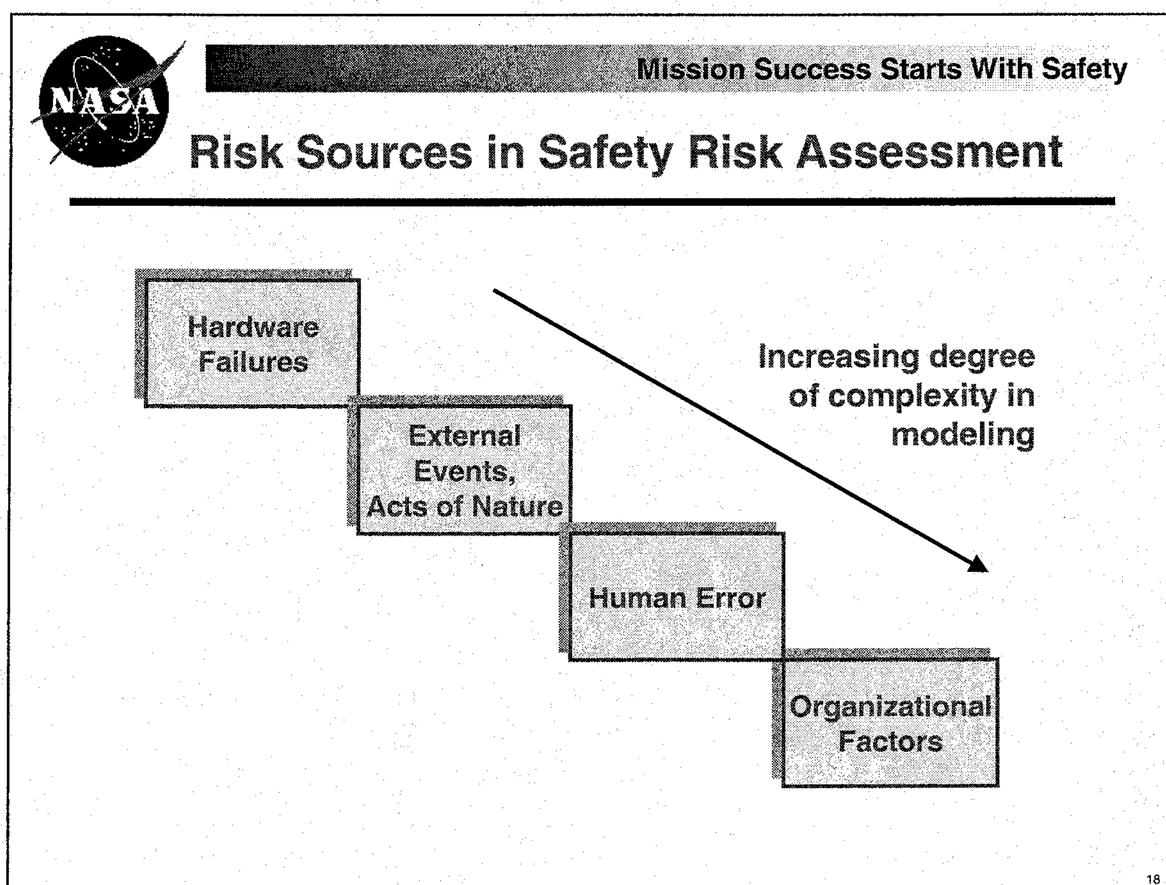


Figure 17

MAJOR NASA PROGRAMS NOW USE PRA

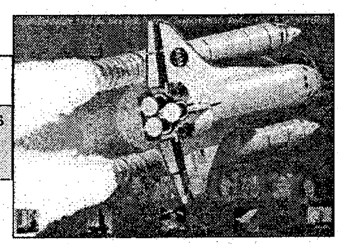
The Space Shuttle and the International Space Station are two major human rated NASA projects for which PRAs are being currently performed. The first one is primarily performed to assist the space shuttle upgrade program. The second one is performed to assist construction, assembly and operation of the international space station, one of the most challenging scientific and engineering challenges of our time. PRA has been used to assign safety goals to the space shuttle program.

Mission Success Starts With Safety

Major NASA Programs Now Use PRA

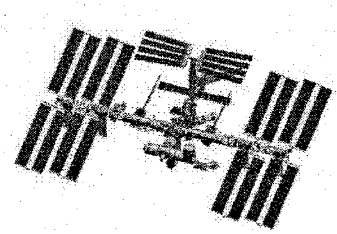
Space Shuttle Development Roadmap

Goals and Objectives	97	02	07	12
1 Fly Safely	1 vehicle loss in 148 flights	1 vehicle loss in 250 flights	1 vehicle loss in 325 flights	1 vehicle loss in 500 flights



International Space Station PRA

- **1999 -- The NASA Advisory Council recommended, the NASA Administrator concurred, and the ISS Program has begun a PRA.**
  - **The modeling will be QRAS-compatible.**
  - **First portion of PRA (through Flight 7A) - delivered in Dec. 2000.**



19

Figure 18

MARS SAMPLE RETURN MISSION

Because it is unknown what types of health or other risks a sample from Mars could pose upon return to Earth, NASA's Planetary Protection Program has preliminarily assigned the probability of one in a million or less that such a sample will contaminate the Earth. This means that the sample should have less than one in a million chance of being opened in an uncontrolled environment upon or after re-entry in the Earth atmosphere. This type of goal cannot be satisfied by any assessment other than a probabilistic risk assessment (e.g., not by any deterministic safety assessment).

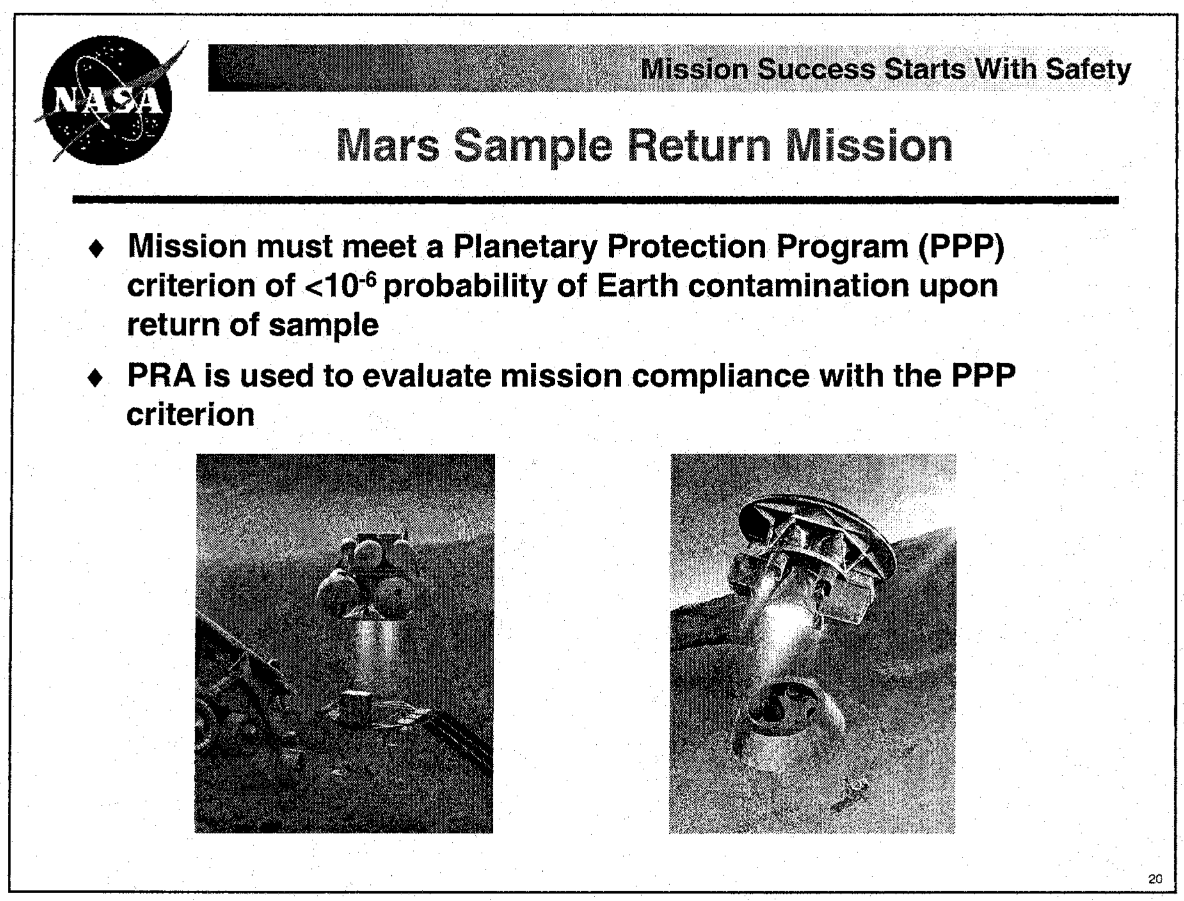


Figure 19

NASA'S UNIQUE PRA METHODOLOGY NEEDS

Although NASA is acquiring or adapting PRA methods, software and data from applications in other industries to the extent possible, NASA PRA applications have some unique features that require special needs and special attention. They include: diversity of project application; multi-phase treatment; unique types of initiators; unique environments; unique types of adverse consequences; special treatment of human and software reliability; etc. These capabilities need to be developed or acquired as soon as possible.

Mission Success Starts With Safety

NASA's Unique PRA Methodology Needs

- Broad range of programs: Conceptual non-human rated science projects; Multi-stage design and construction of the International Space Station; Upgrades of the Space Shuttle
- Risk initiators that vary drastically with type of program
- Unique design and operating environments (e.g., microgravity effects on equipment and humans)
- Multi-phasing approach in some scenario developments
- Unique external events (e.g., micro-meteoroids and orbital debris)
- Unique types of adverse consequences (e.g., fatigue and illness in space)
- Different considerations for human reliability (e.g., astronauts vs. other operating personnel)
- Greater importance of software reliability
- Specialized database needs

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Figure 20

END STATES FROM ISS PRA

Examples of unique PRA end-states can be seen in the International Space Station (ISS) PRA: loss of station; loss of crew; evacuation end states, and other undesired end states like loss of module; loss of system; or collision between a US or a Russian logistic vehicle and the ISS.

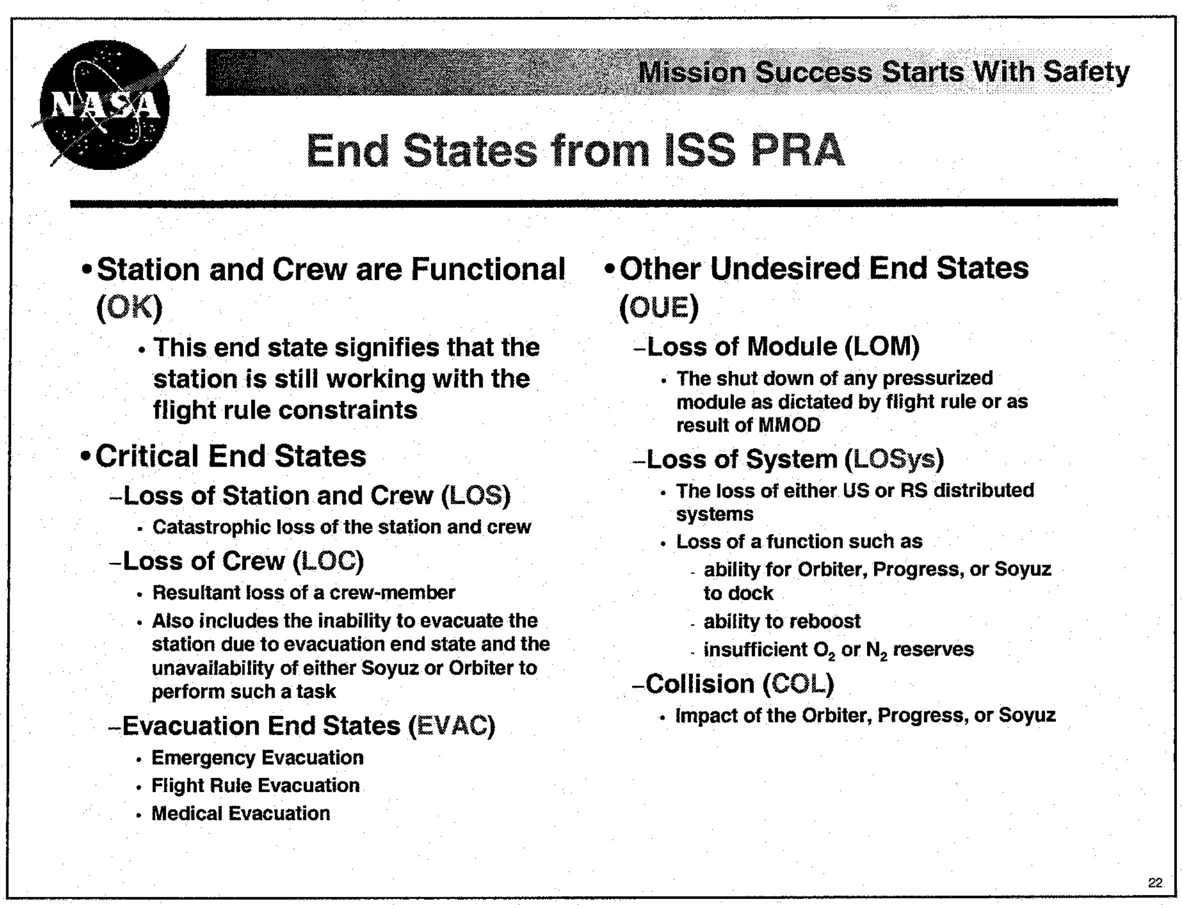

Figure 21

INITIATING MEDICAL EVENTS FROM IS PRA

The ISS PRA also demonstrates the need for special types of initiating events that are normally not dealt with in ground based systems or facilities. Medical initiating events due to illness or adverse environment in space are examples of unique types of initiators that may be encountered in NASA PRA applications.

Mission Success Starts With Safety

Initiating Medical Events from ISS PRA

- **Medical disorders quantified are for "severe" injuries or illnesses only**
  - **those that would normally require hospitalization on Earth**
- **Medical categories are:**
  - **Circulatory**
  - **Dermatology**
  - **Digestive**
  - **General Internal Medicine**
  - **Genitourinary**
  - **Infectious Disease**
  - **Neurology and Psychology**
  - **Respiratory**
  - **Trauma and Poisonings**

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Figure 22

ENERGETIC HAZARD ESD EXAMPLE (ISS PRA)

Another example of a unique type of initiator in a NASA PRA is impact with micrometeoroids or orbital debris. Such impact with ISS systems and components can lead to very severe consequences to the space station and its personnel. Equally severe consequences can result from this type of collisions with ISS personnel performing extra-vehicular activities. NASA has a number of computational models and tools for conducting probabilistic assessment of these types of collisions and associated risks to hardware and ultimately to ISS personnel.

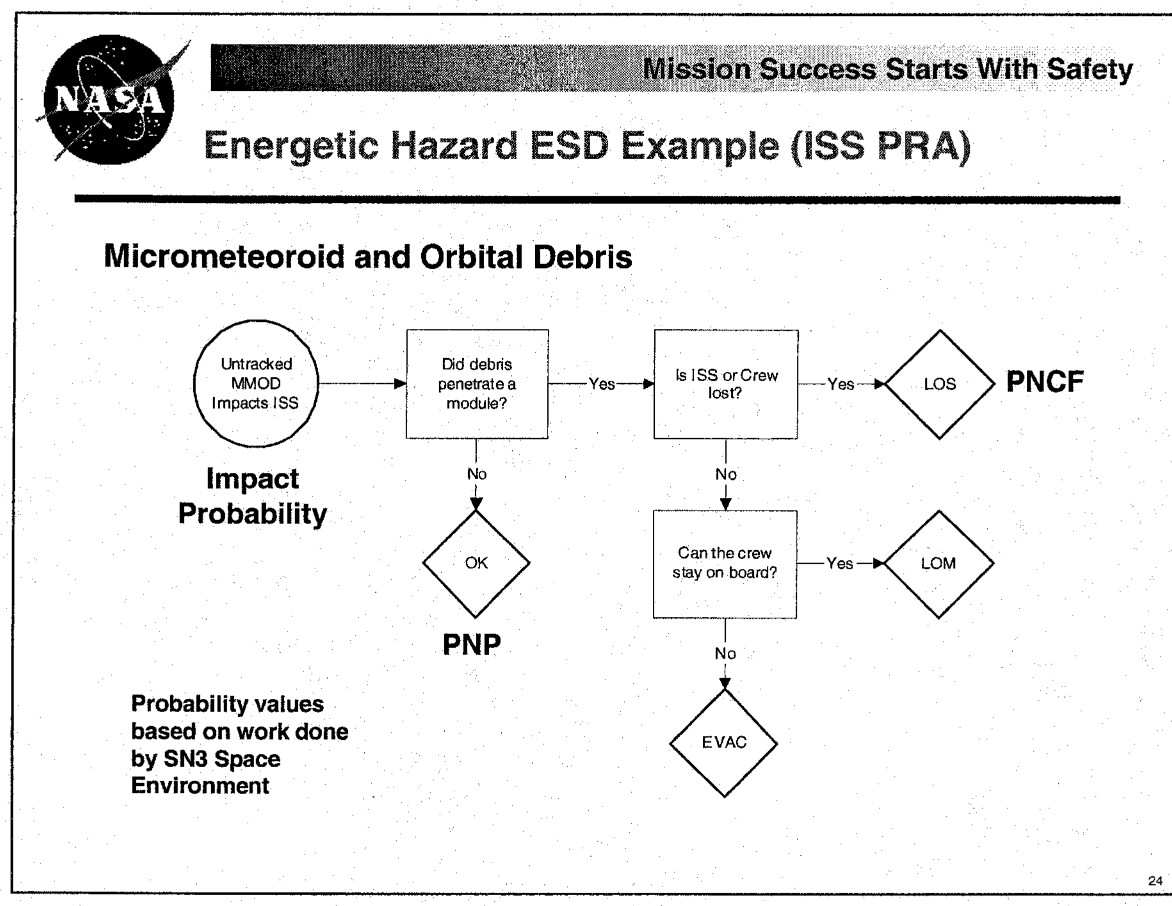

Figure 23

GOALS FOR THE FUTURE

Our vision for future PRA use at NASA shows not only a world-class capability to perform PRA for all applications for which this method is appropriate but also the creation at NASA of the right culture and environment to make the best use of PRA in all or most management decisions that impact mission success, performance improvement, safety enhancement and costs.

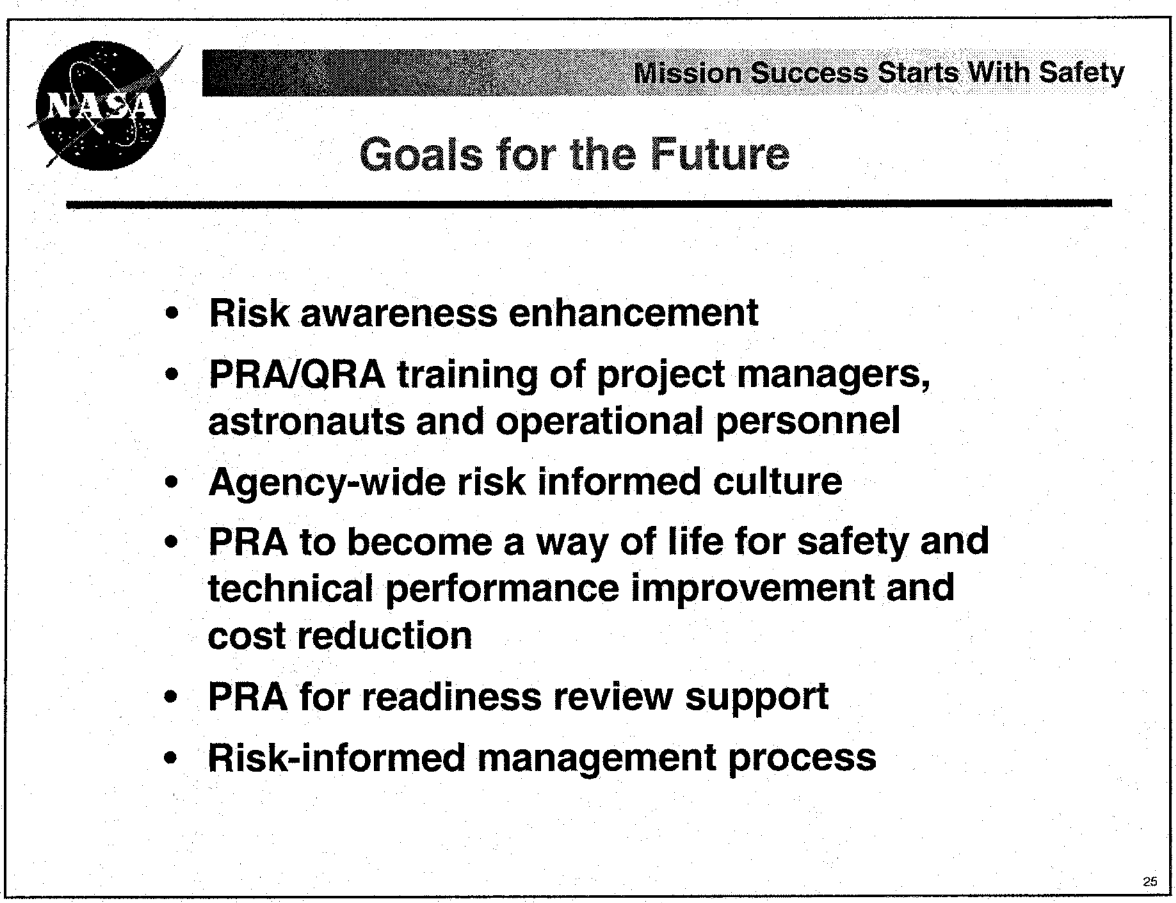

Figure 24

"Losses to Society and Opportunities for Companies"

Dr. William J. Bellows
Experimentation & Learning Network
Rocketdyne Propulsion & Power
The Boeing Company
Canoga Park, CA 91309-7922

"LOSSES TO SOCIETY AND OPPORTUNITIES FOR COMPANIES"

At the heart of "non-deterministic" methods is the inclusion of variation in engineering calculations. Unlike engineering calculation examples in textbooks, demonstrating exact dimensions, material properties, and boundary conditions, these calculations are effectively made inaccurate by variation. Given variation in input conditions, answers resulting from the associated engineering calculations will also exhibit variation. The certainty desired from deterministic methods implodes because it excludes variation and is replaced by the uncertainty of non-deterministic methods. Embedded in this presentation is an introduction to efforts underway Boeing to foster a greater degree of awareness of variation in everyday activities. The title of this presentation is a reference to the opportunities that exist to "reduce loss to society" when companies develop a deeper appreciation of variation, including its sources (connections and systems) and its consequences.

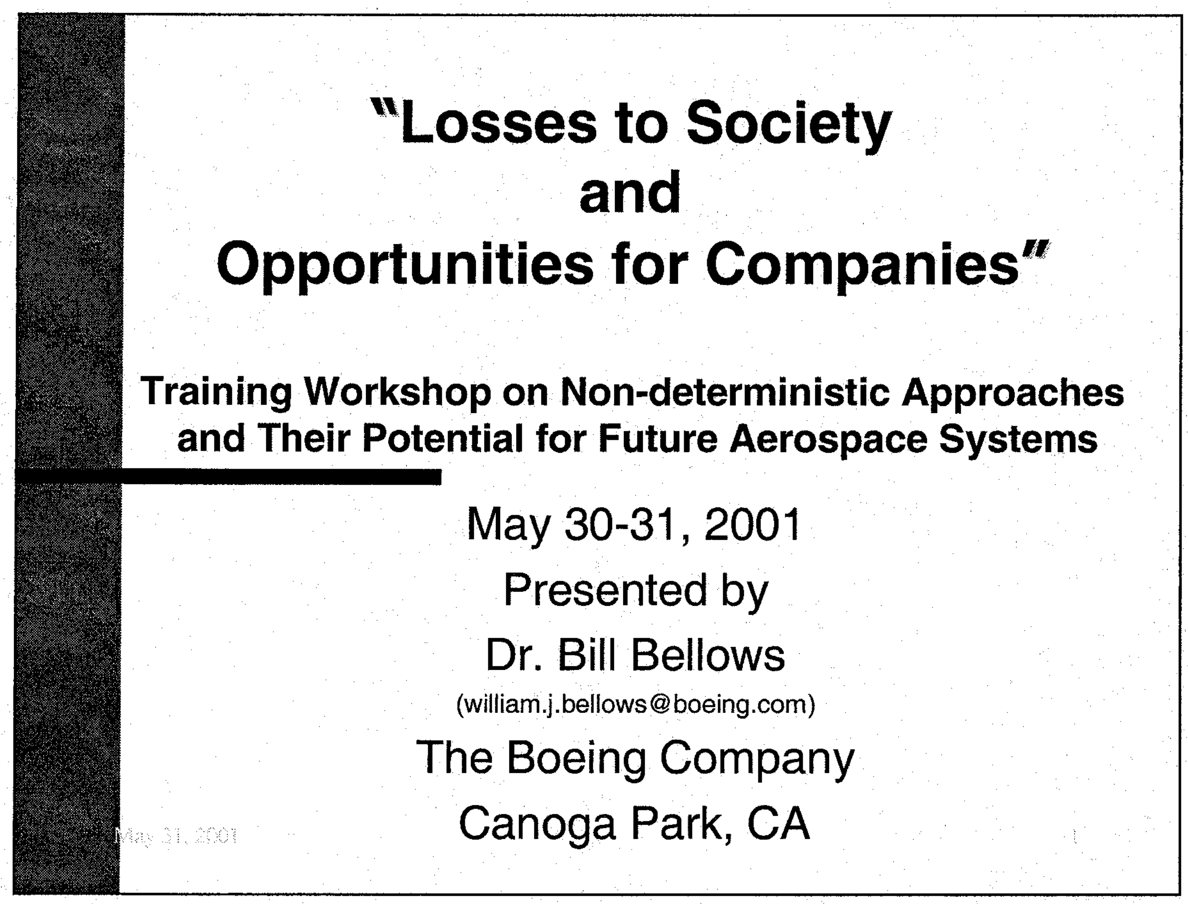

Figure 1

AGENDA

This overview presentation will include a statement of the objectives, a review of assumptions, a simple systems thinking exercise involving woodworking, an introduction to investment thinking, and a vision of the potential of "better thinking" about variation, systems, psychology, and the theory of knowledge.

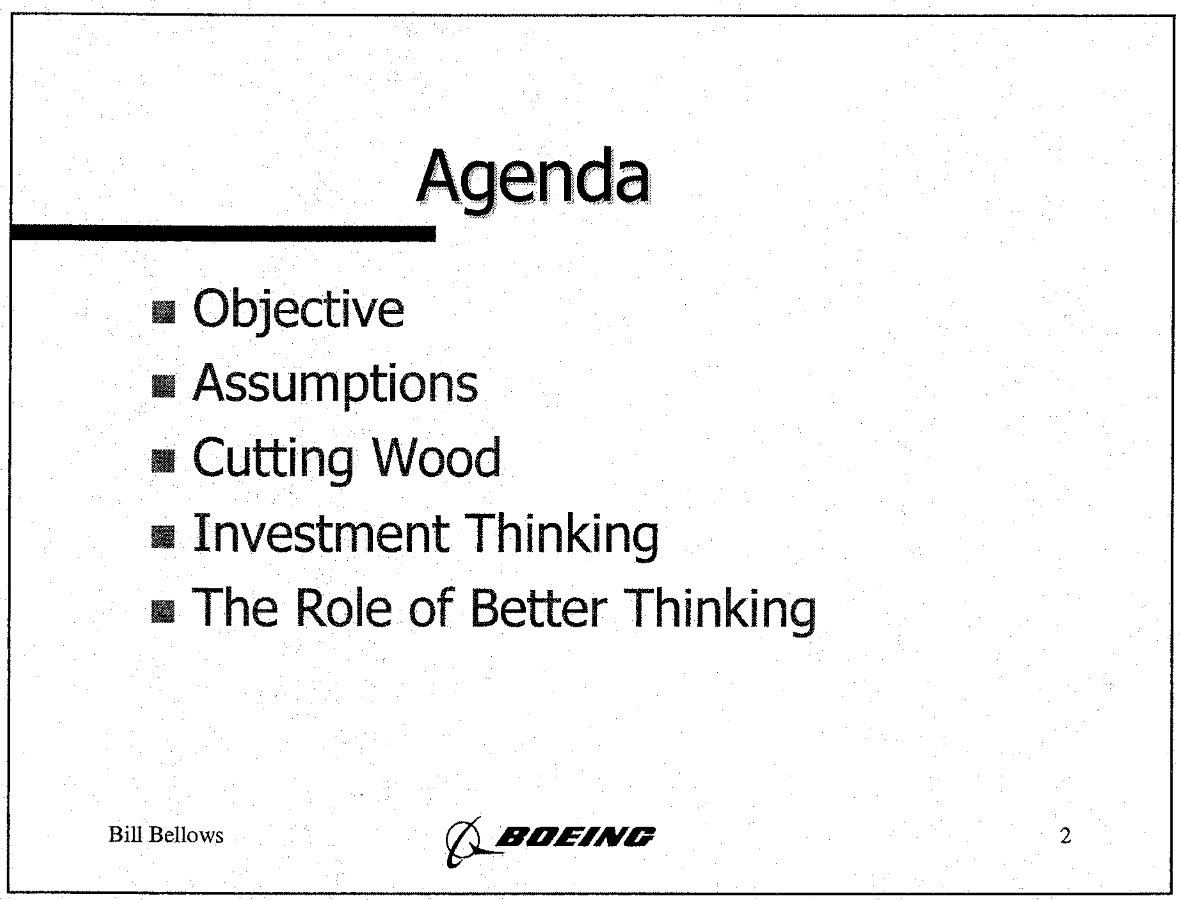

Figure 2

OBJECTIVE

The material presented in this overview is an accumulation of 15 years of reflection on management theories contributed by Charles Kepner, Benjamin Tregoe, W. Edwards Deming, Genichi Taguchi, and Peter Senge, among many others. My first exposure to these "change leaders" was the problem solving and decision making analyses of Drs. Kepner and Tregoe, to be followed soon after by the work of Dr. Taguchi and Dr. Deming. In repeated applications involving highly visible problem resolution activities, the potential energy of Taguchi Methods became more and more evident. The early applications also revealed the narrow focus of these applications – to fix or repair products and processes. An obvious application pattern was developing. In borrowing from the concepts of Dr. Deming, a theory was developed to explain why this costly application pattern was widespread across industries. Dr. Deming's management theory provides an explanation for how organizations can develop higher levels of working together. The objective of this presentation is to offer a view of the potential energy offered by the synergetic linkage of these varied management theories.

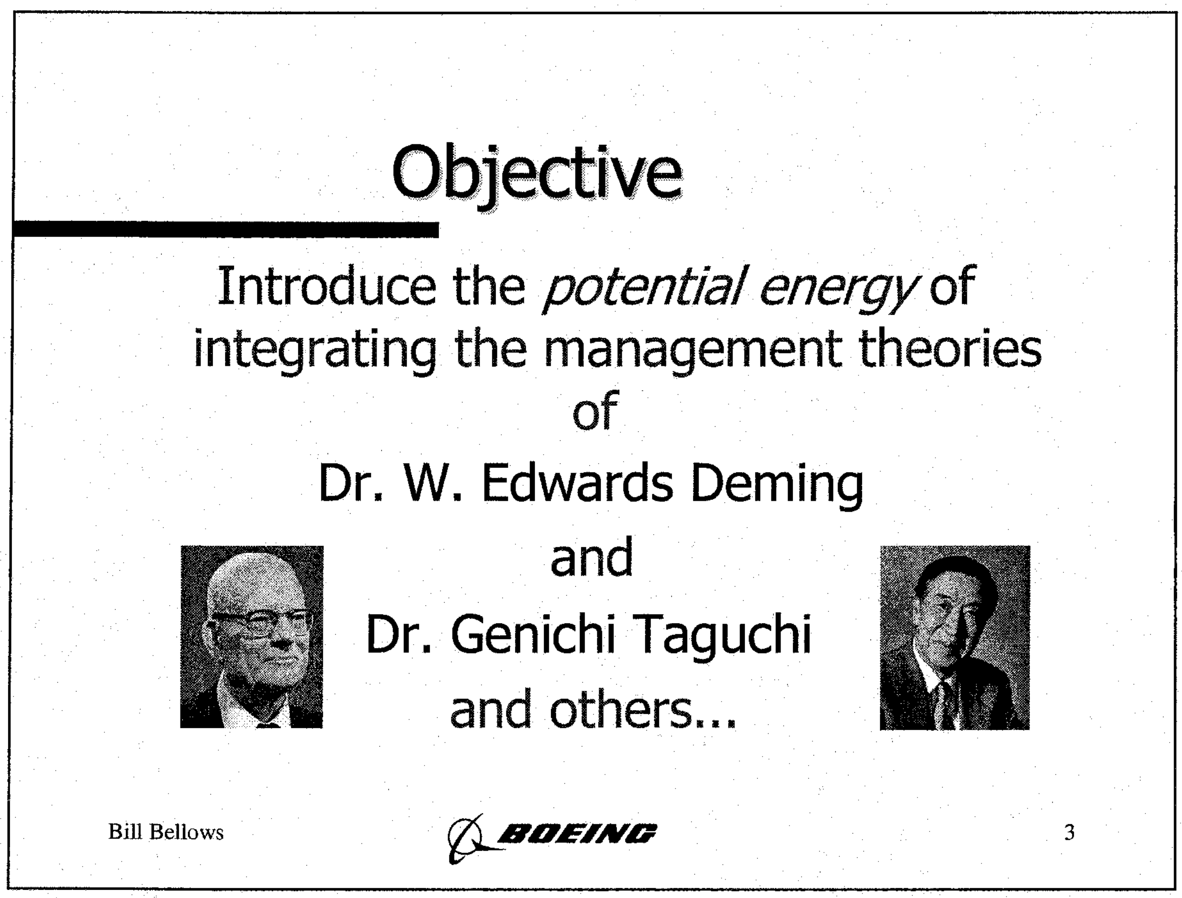

Figure 3

3-D DIFFUSION EQUATION

My engineering background has its roots in heat transfer analyses, solving this partial differential equation to establish the temperature distribution of an object under a variety of boundary and initial conditions. The terms of the equation include a "diffusion" component on the left side to represent the effects of three-dimensional heat conduction. The "Q" component is the so-called energy "source term", included as an indication of the magnitude of "energy generation" within the object. The right side of the equation is the sole time-dependent term; an indication of temperature changes over time. As will be shown in the closing chart, my awareness of these three terms has provided general guidance in the diffusion of better management theories.

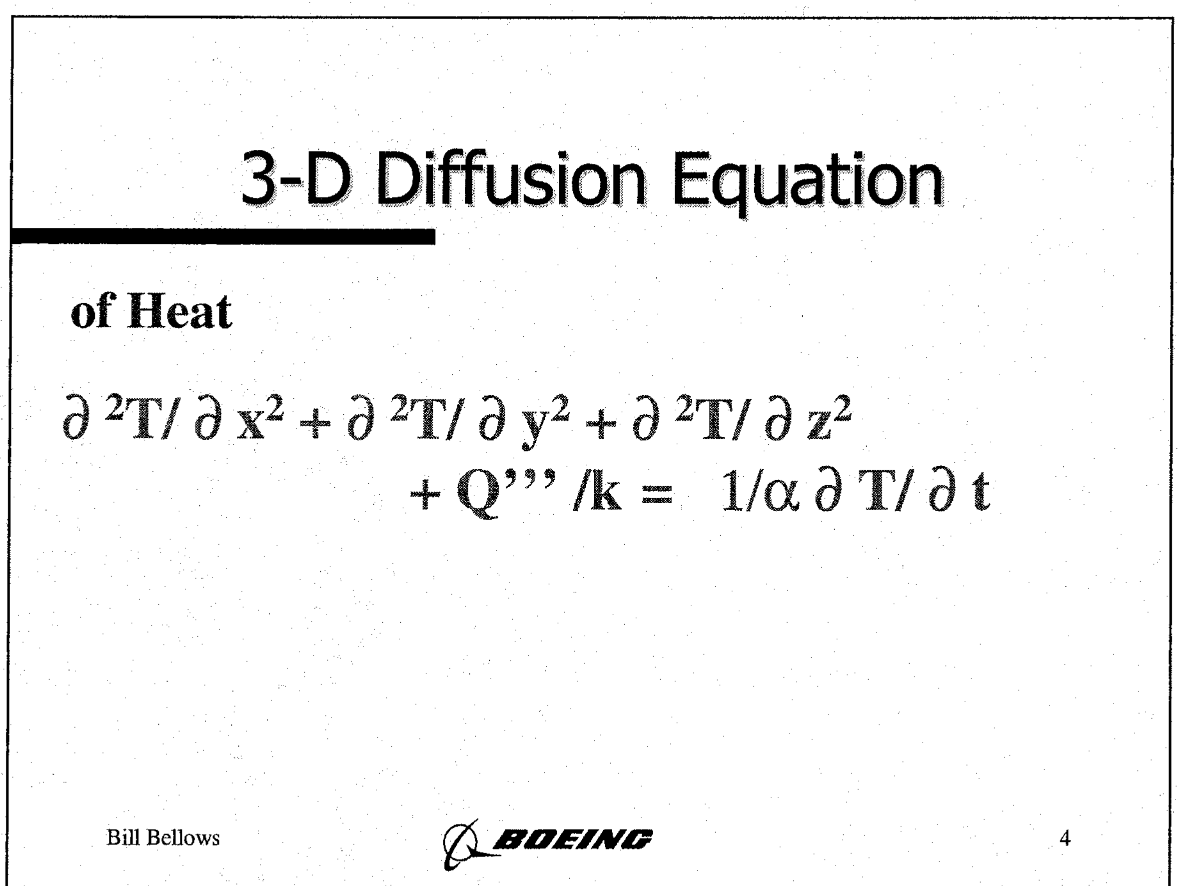

Figure 4

QUALITY LOSS

Dr. Taguchi has uniquely defined quality in terms of "minimizing loss to society". This presentation will offer a view of ongoing activities at The Boeing Company to promote *better thinking* as a means to achieve *better doing*, which can be translated into minimizing losses to society and Boeing. These efforts involve a focus on variation management, seeing systems, and *investment* thinking.

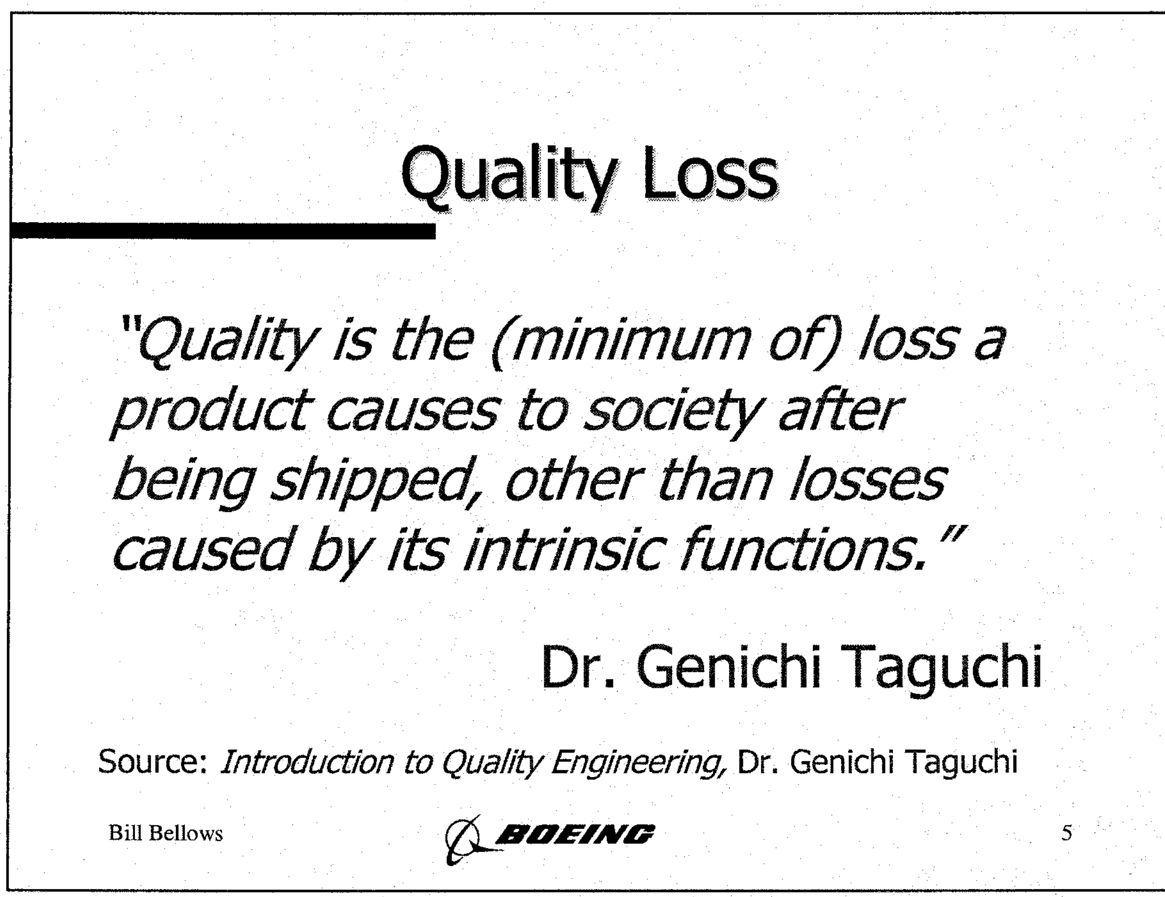

Figure 5

PERCEPTION & THINKING

Tom Johnson, a professor of Quality Management at Portland State University, offers as a ponderable that "what we see" is a reflection of "how we think". As a simple example, consider the response of a parent upon reading their child's report card. Are the grades, low or high, an indication of the student, alone? Or, might it be possible that the grades are an indication of the "education system" in which the child resides, a system that includes the student, the teacher, the parents, and the hiring practices of the local board of education, to name a few inter-dependent parts. How the parent responds to their child's report card will reveal their understanding of the size of the child's education system and the degree of interconnectedness of the components. Likewise, in a factory setting, the quality of a duct weld is a reflection of the welding system in which the welder resides.

Perception & Thinking

"How the world we perceive works depends on how we think.

The world we perceive is a world we bring forth through our thinking."

H. Thomas Johnson

Bill Bellows BOEING 6

Figure 6

UTILIZATION OF THINKING

In the spirit of thinking about interconnections and systems, consider the logic of routinely asking questions such as "Where are we going?" Where does this fit in?" "Where did this come from?" "What is my role?" and "What is this part of?" To ponder them routinely is to be reminded of a general pattern of inter-dependence that surrounds all of us. The last question, "Where should we invest?" explores the implications of systems thinking, when coupled to economics. The concept of connections is fundamental to recognizing the relationships between upstream, local, and downstream conditions.

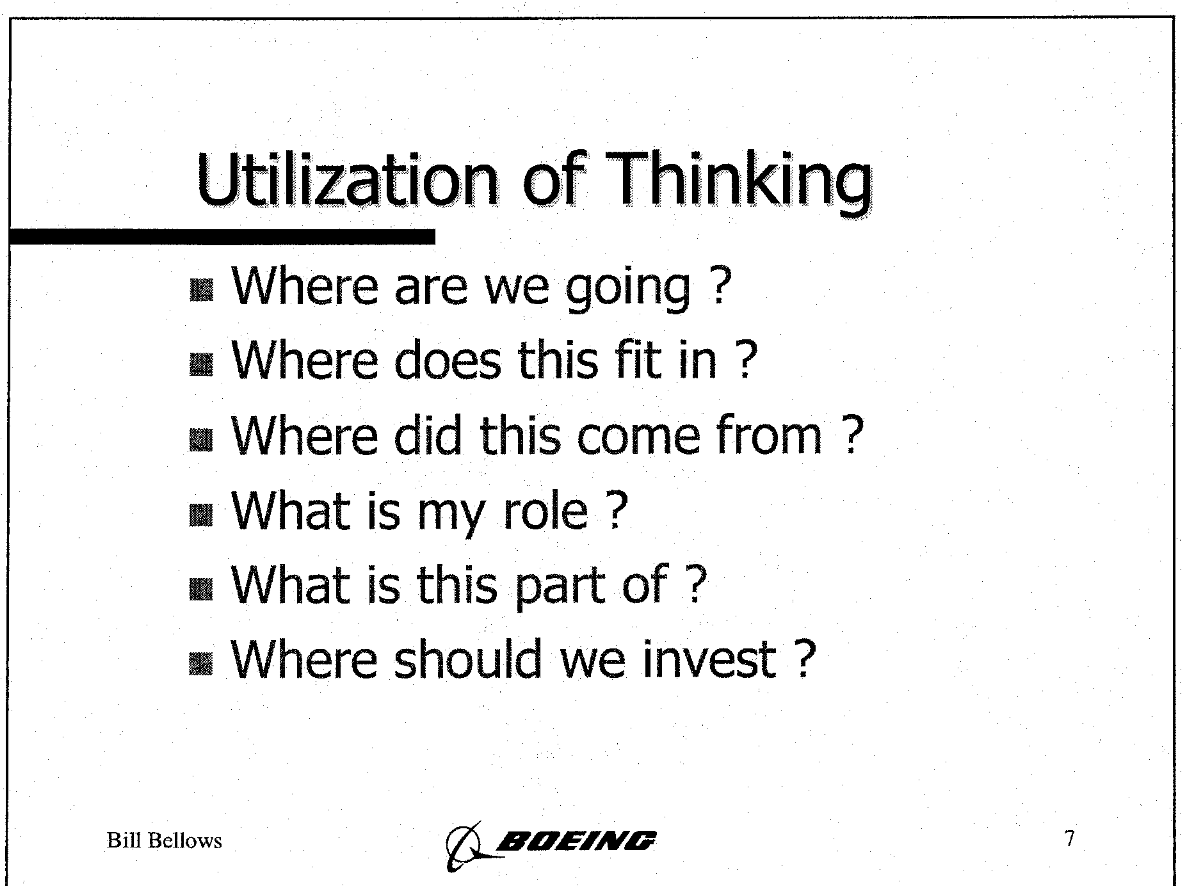

Figure 7

ASSUMPTIONS

From my reflection on a 15-year review of management theories, I would like to propose three progressive assumptions; 1- A better way to operate an organization is to invest resources with the ability to delight customers, 2- Better investment results from discovering opportunities to invest, and 3-The discovery of opportunities for investment is limited by how thinking is conditioned.

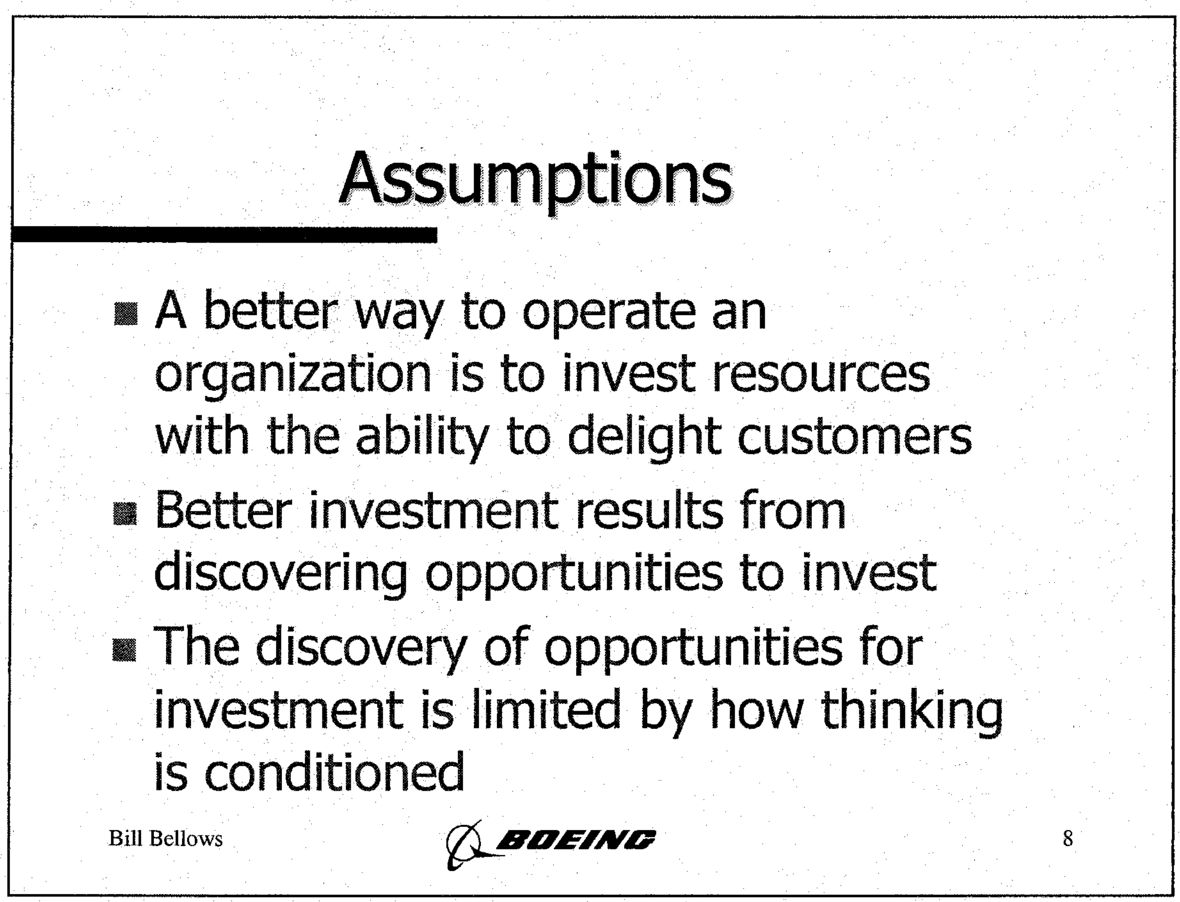

Figure 8

WHAT IS NEEDED?

My conclusion is that we are in need of better thinking, that is - "thinking that promotes better discovery." Discovery of opportunities, discovery of connections, discovery of systemic effects, to name a few forms of needed discovery. If one cannot see connections, then one can see only parts. As such, our lives and the world we live in are viewed as sets of fragmented pieces. Without a sense of connections, we are resigned to being reactive. We tend not to "see things coming" and, consequently, experience problems without warning. Adding to this scenario of disconnections, we then act to impart blame to elements of the system instead of to the system itself. Such blame may be imposed on the student in a classroom or on the welder on a shop floor. If only we could see connections, we could anticipate. Such anticipation provides early warning of impending trouble and the ability to *pro-act*. Better thinking offers the ability to uncover these opportunities for investment.

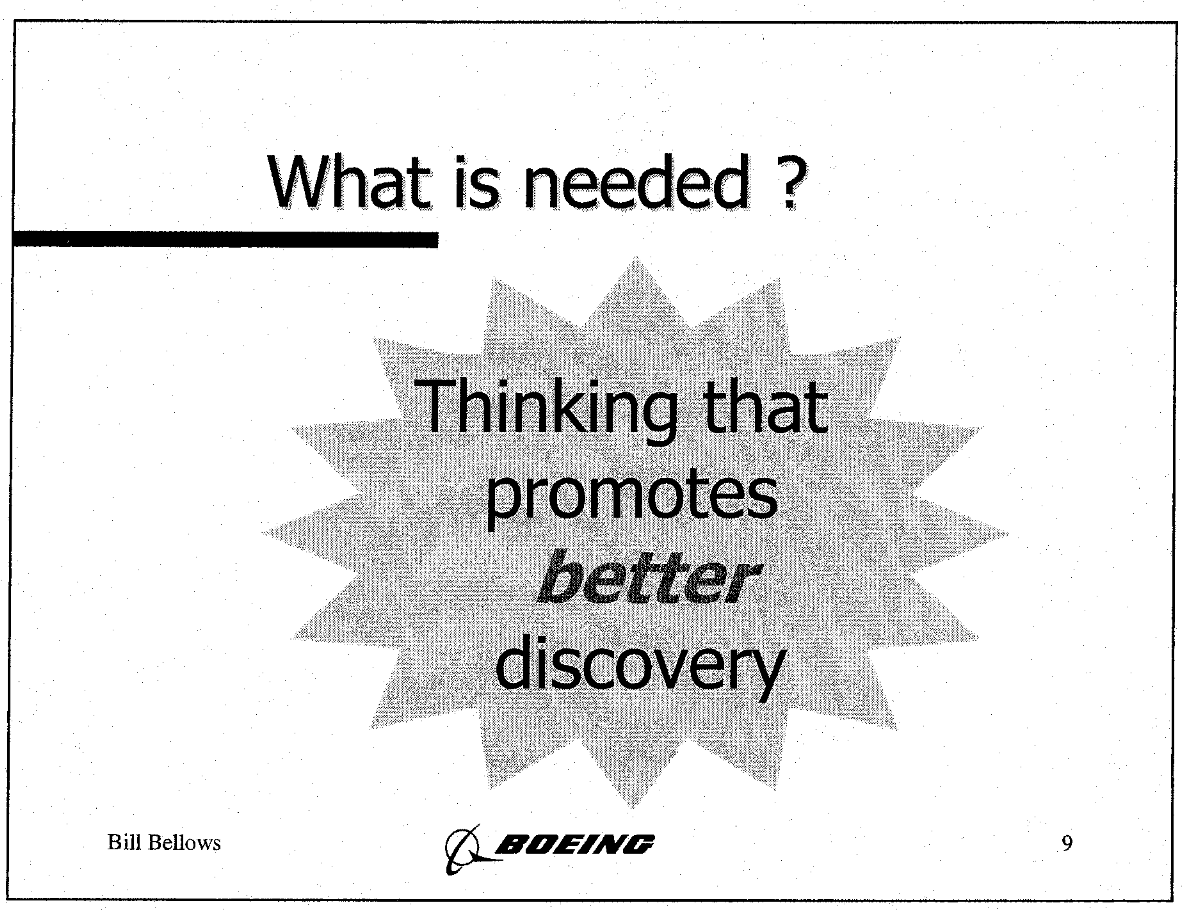

Figure 9

QUESTION

Consider the simple question, "What is this part of?" Imbedded in this question is an explicit reference to a connection. The systemic thought is revealed by the concept "part of", as opposed to "part". Without the "of", we could only inquire about the part, as in the question, "What is this part?" Given this inquiry, the connections would be lost as we return to a worldview of "fragmented pieces".

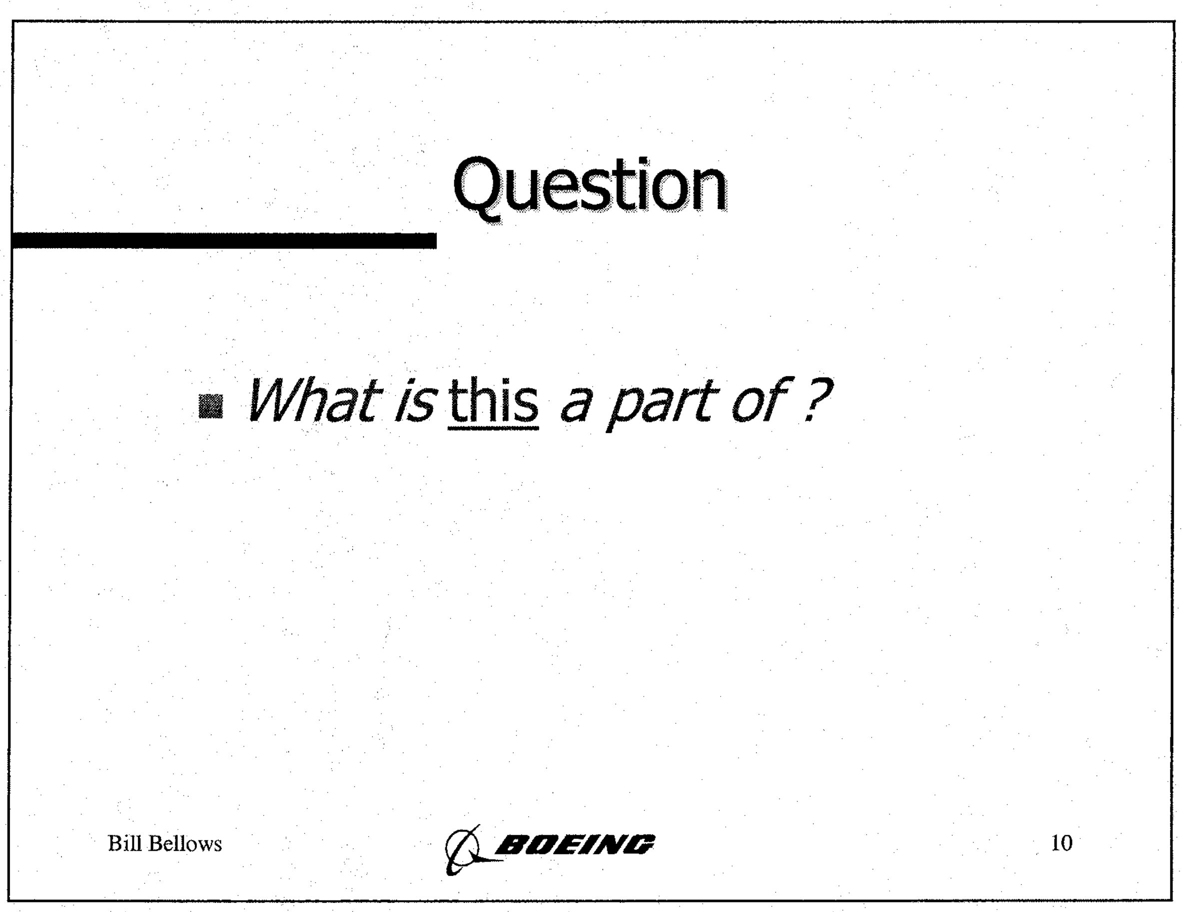

Figure 10

WATER AND ROCK LOGIC

In reference to the "from-this-to" sequence, questions such as "What is this part of? Where did this come from?" and "What will this lead to?" represent the essence of understanding relationships and inter-connections. The thinking revealed by these questions has been termed "water logic" by the noted "thinker" and author, Dr. Edward de Bono. By contrast, references to events, parts, and pieces, are termed "rock logic". To view the world with "rock logic" is to view it in the form of an "exploded view" - parts without connections. To view the world with "water logic" is to view without seeing parts. Such a view reveals the world to be a pattern of relationships and linkages.

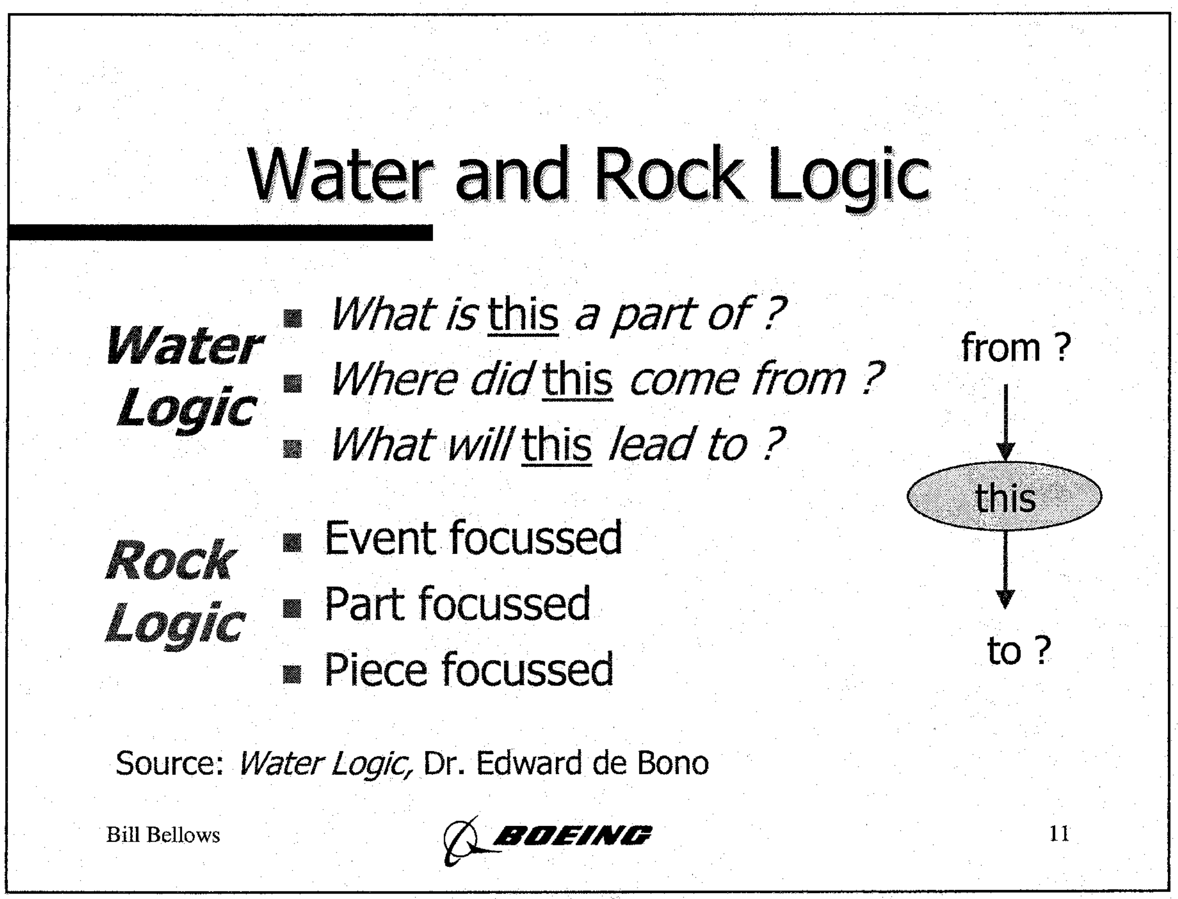

Figure 11

QUESTION: CUTTING WOOD

To better appreciate the implications of water and rock logic, of parts and connections, consider the routine of cutting a piece of wood. Taking a step back, imagine your actions associated with a woodworking project - all in the confines of your garage. Your project is nearing completion as you search for a short piece of wood. The closest piece you can find is a tad too long, necessitating the need to make it shorter. In rapid order, you measure the length that is required, mark the wood to cut it, and get ready to start the electric saw. Before the piece is shortened, I look at the top face of the piece to see "how many lines are drawn completely cross the face, top to bottom?"

"How many lines would you draw?"

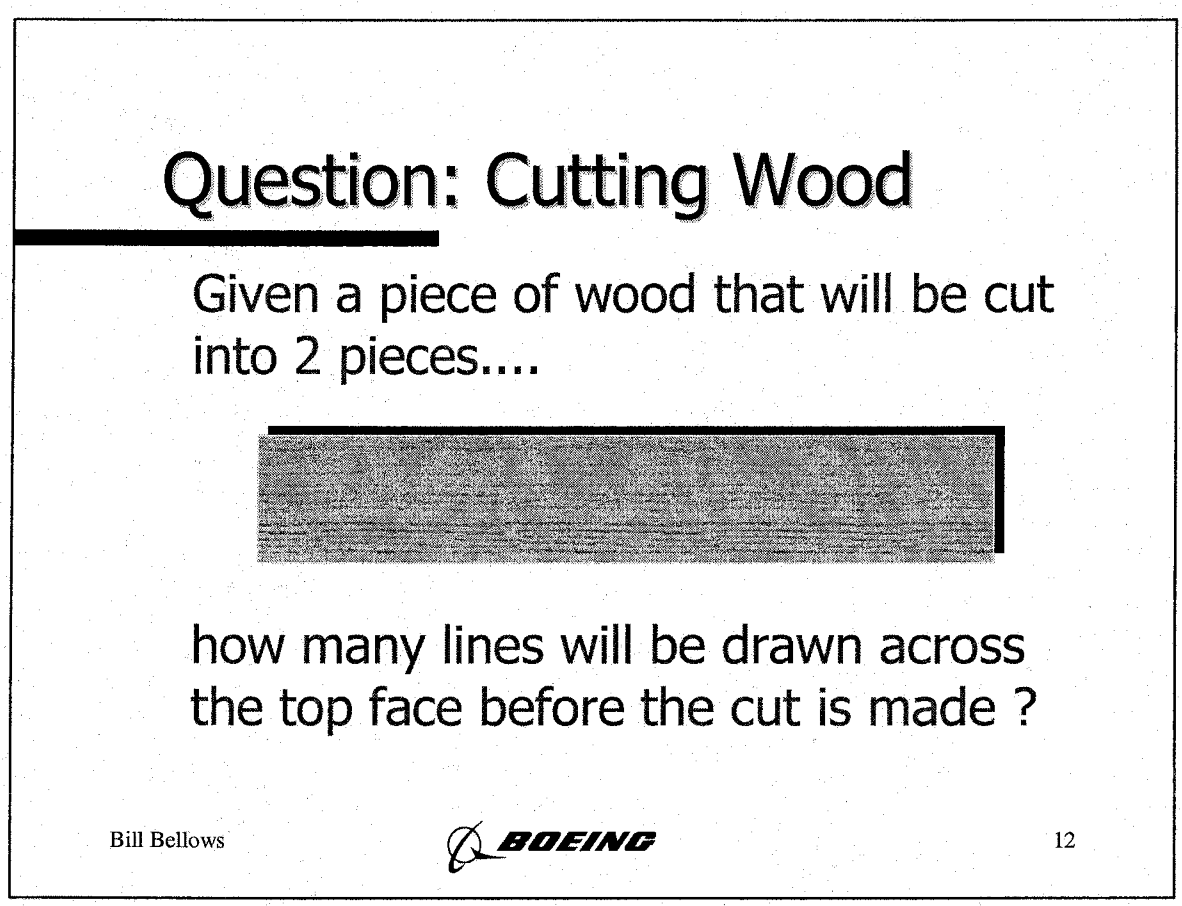

Figure 12

QUESTION: CUTTING WOOD

Hopefully, to no surprise, the most frequent answer (with bare exception) is "one line". The term I use for the thinking that results in this answer is "1-line" thinking.

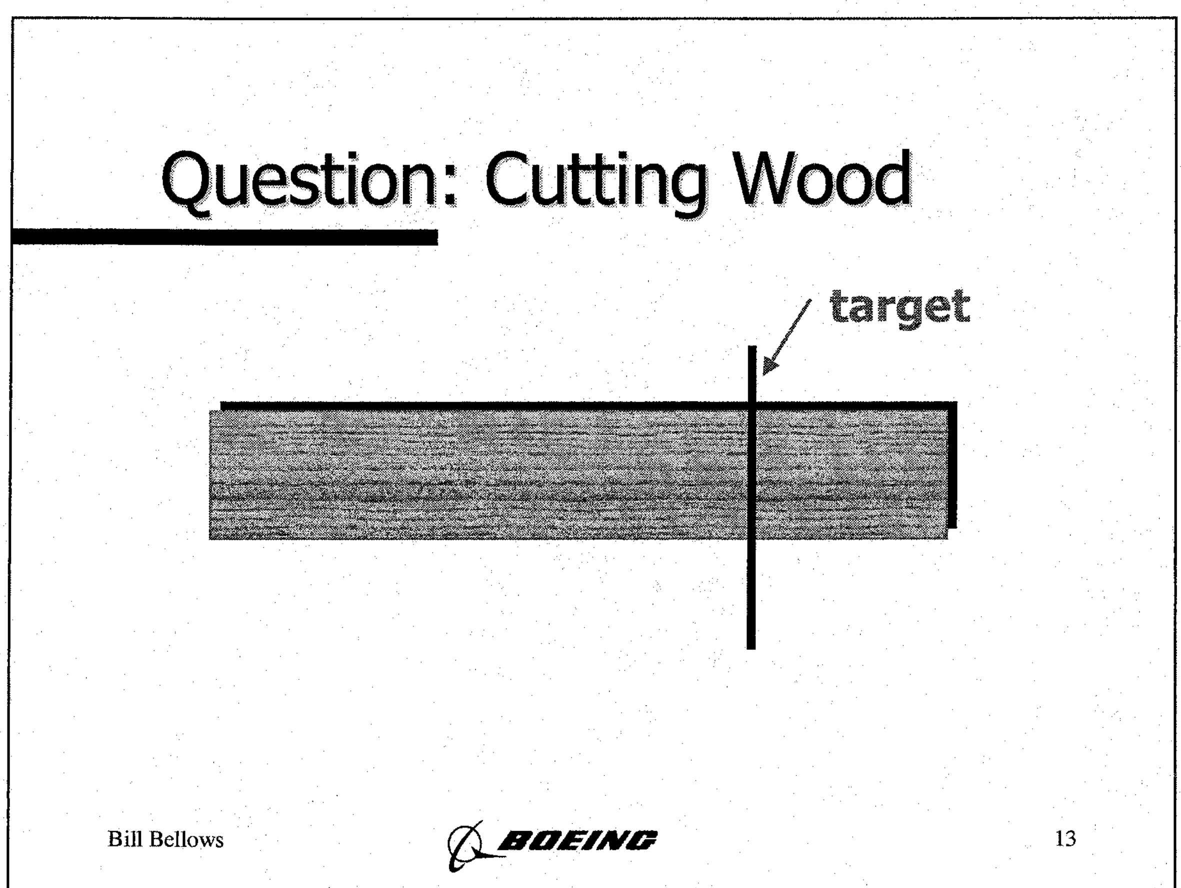

Figure 13

QUESTION: CUTTING WOOD

Is “1 line” the correct answer? If not, “What other answer could there be?” While it is not immediately obvious, other answers might be “2 lines” or “3 lines”, if not more. The terms I use for the thinking that results in these answers are “2-line” thinking, “3-line” thinking, and so on.

What is a possible explanation for the “1 line” answer? Surely, it is but one of many possible answers. Could it be that we would draw one line out of habit? Why is the habit not “2 lines”? I would offer that the “1 line” answer is an indication of a strong intuitive sense of water logic - knowing what the piece of wood is “part of”, knowing where “it came from”, and knowing where it “will lead to”. Such a perspective is likely when one is involved in a home project and connections are visible as well as conscious. How visible are the connections in a work setting, where the connections are less visible?

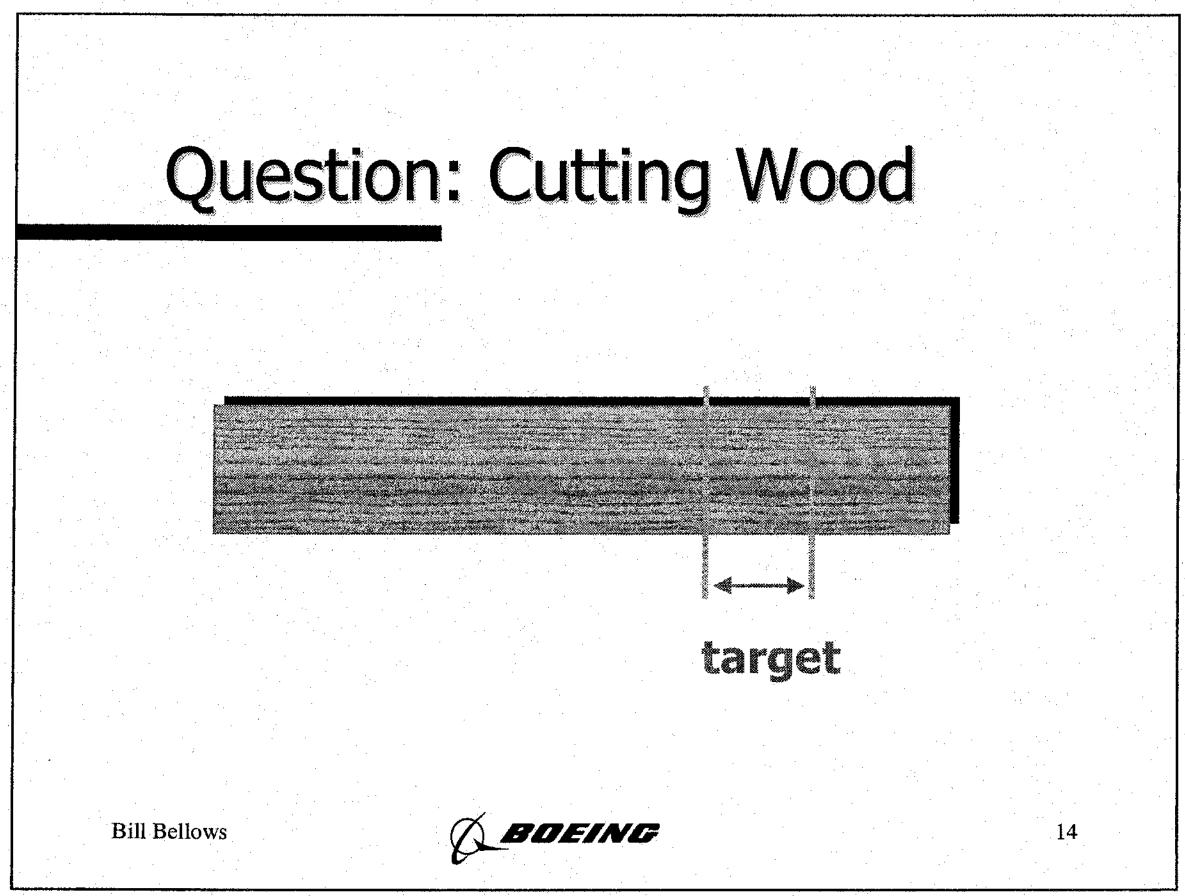

Figure 14

RELATIONSHIPS

I would like to now offer an explanation for the habit of "1 line" thinking when cutting a piece of wood for a home project (step 1). Consider the x-y axes shown, with a part characteristic as the horizontal axis and the "cumulative negative impact to others downstream" (steps 2 and 3) as the vertical axis. This "negative impact" to others is reflective of Dr. Taguchi's concept of defining quality as the "minimum value of loss imparted to the society". Could it be that we intuitively appreciate the implications of "loss imparted" and act to minimize this loss (this impact) when we are the next person in the flow, as if receiving our own work? Might we act with a sense of water logic? I believe so. Could it be that we are not as particular and will not focus on target, but rather on "meeting the requirements of a tolerance" when we are not the next person in the flow? Without the sense of a connection, might we act with "rock logic" and default to a part perspective? I believe so.

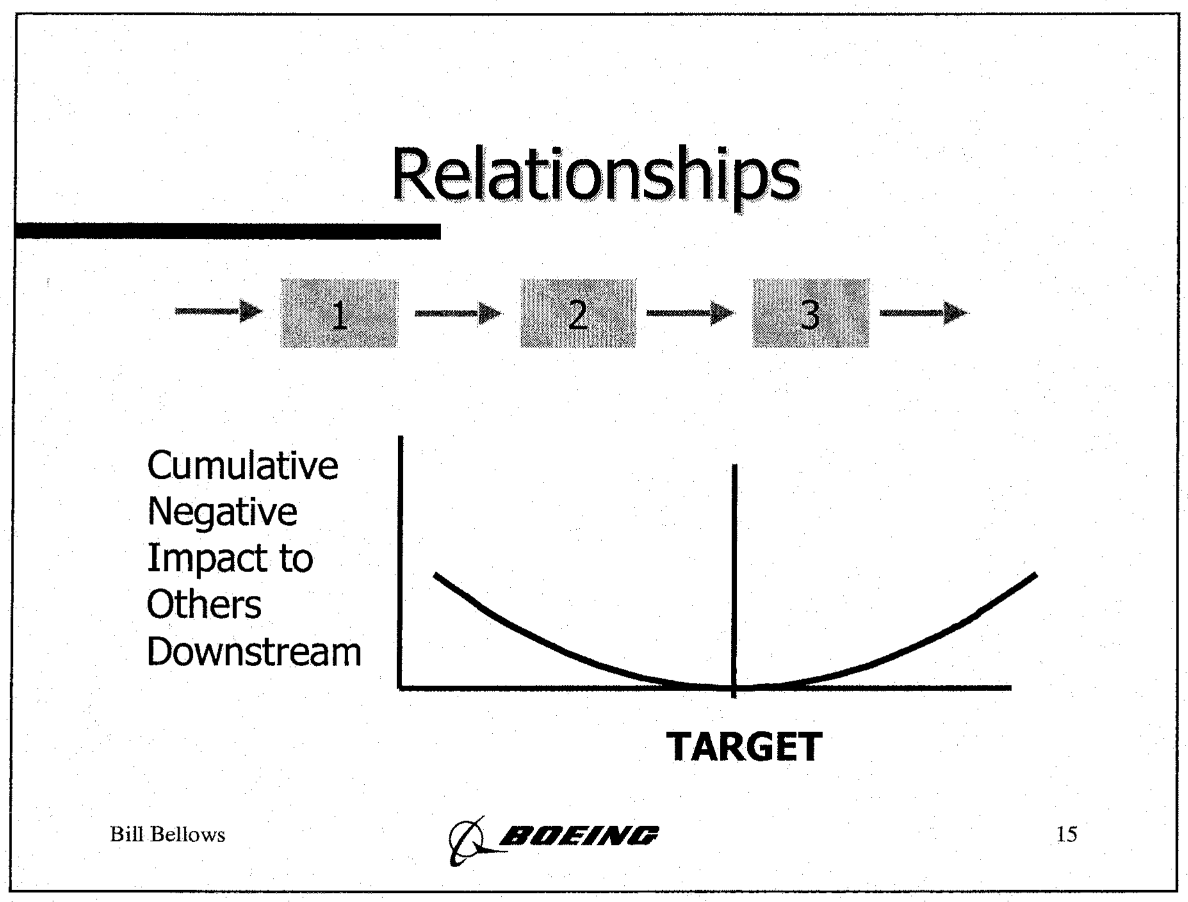

Figure 15

INVESTMENT THINKING

A stitch in time that saves nine. An ounce of prevention that is worth a pound of cure. What these two adages have in common is an awareness of connections - a sense of water logic. Notice also that the *pro-action*, the stitch and the ounce, are far cheaper than the nine stitches or the pound of cure. To act in this manner, with a consciousness of connections, is to practice the economics of "investment thinking".

The general attributes of investment thinking are an allocation of resources (time, money, etc.) to prevent a greater expenditure of resources, or to cause a greater gain in resources. Both scenarios are heavily dependent on water logic. Lacking consciousness of connections, as in a rock logic view of activities, such investment opportunities would be overlooked. Yet another reminder of the need for better thinking.

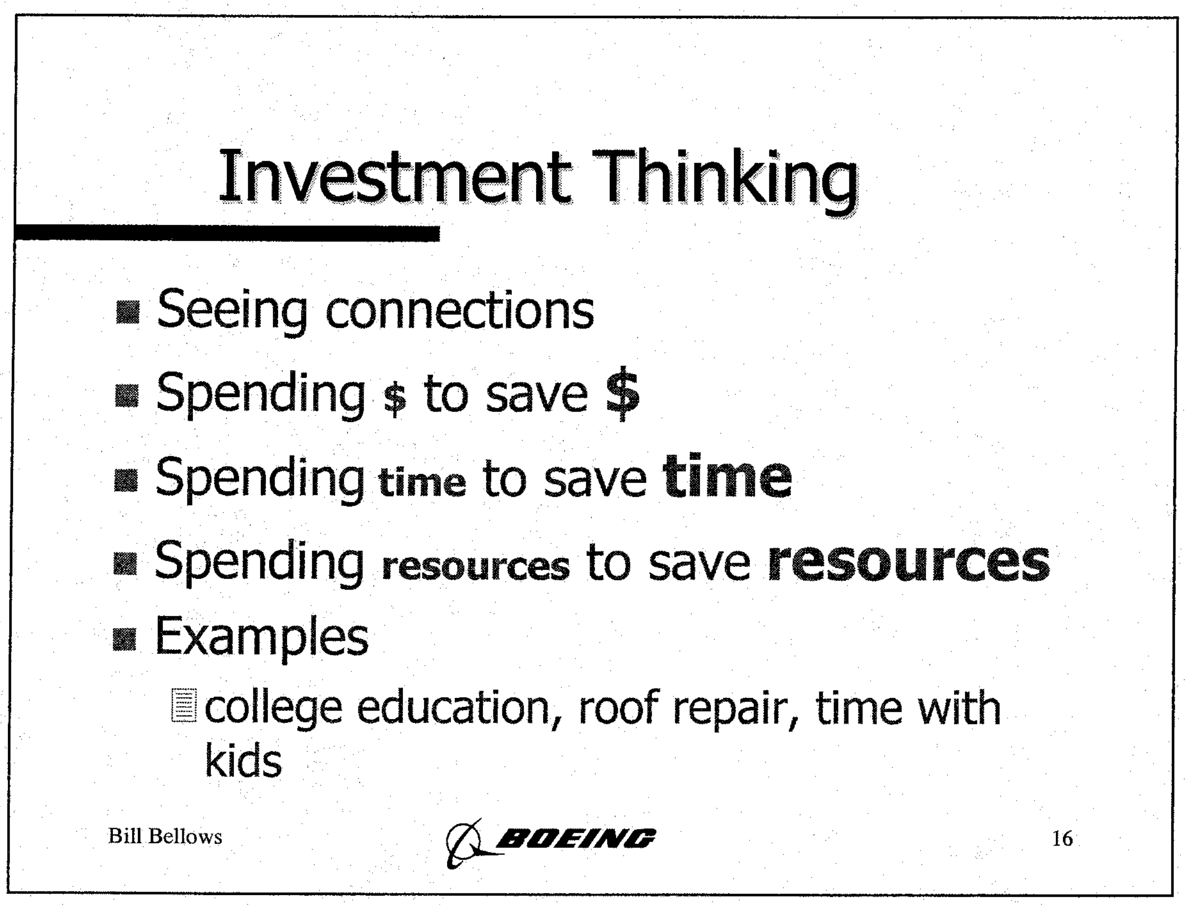

Figure 16

PICKING` UP NAILS

Spending time to save time, as in picking up nails to prevent the flat tire. Another example of investment thinking. To do so is to "minimize loss to society" and be reminded of Dr. Taguchi's concept of quality. Another reminder that the discovery of "investment opportunities" is limited by our ability to see connections - to appreciate water logic.

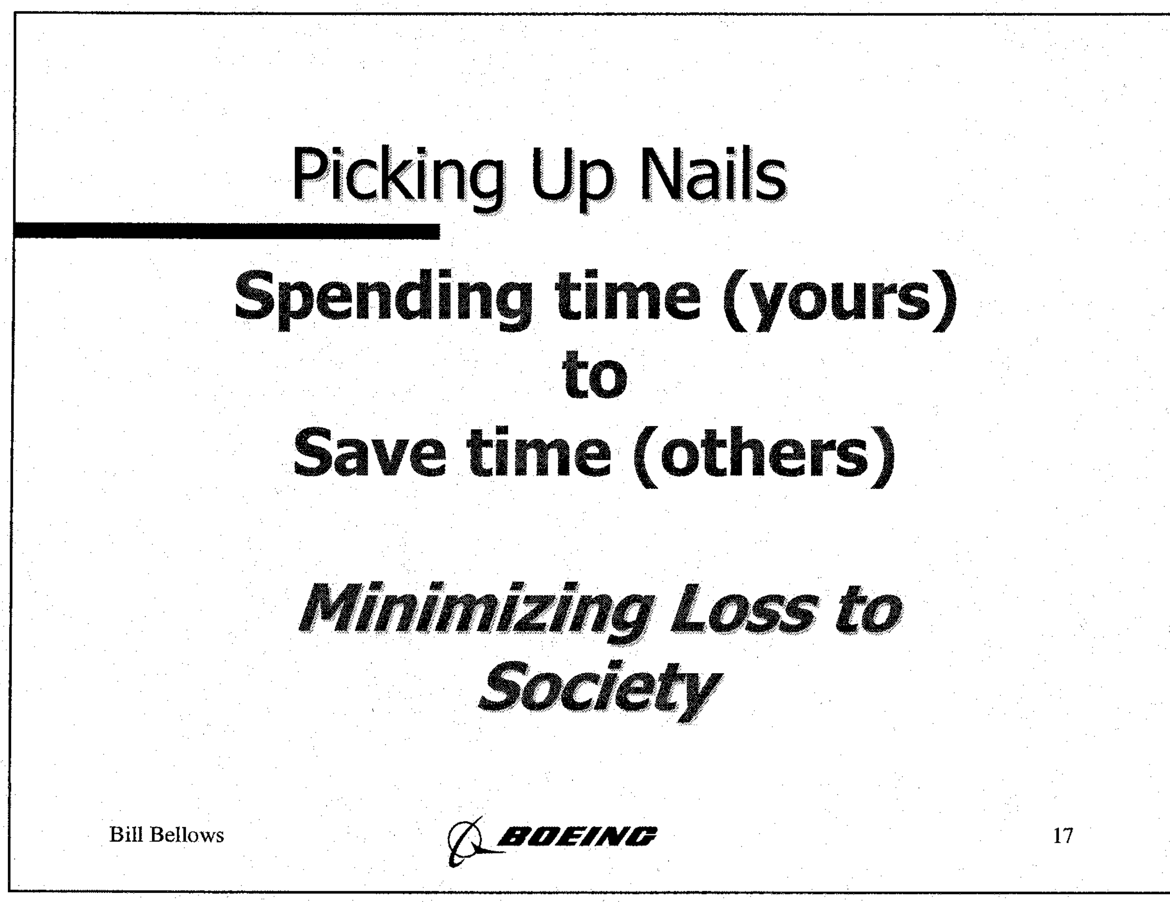

Figure 17

SEEING ORGANIZATIONS AS SYSTEMS

In 1950, Dr. Deming was invited to Japan to meet with engineers and executives from hundreds of companies. As an introduction to an 8-day course in quality control he introduced his audience to the concept of “seeing organizations as systems”. He encouraged them to see their organizations with a sense of flow, of water logic, and be mindful of the continuity in the connections between the activities.

Organizations that practice investment thinking on a continuous basis will generate a continuous series of returns of resources in exchange for a smaller allocation of resources.

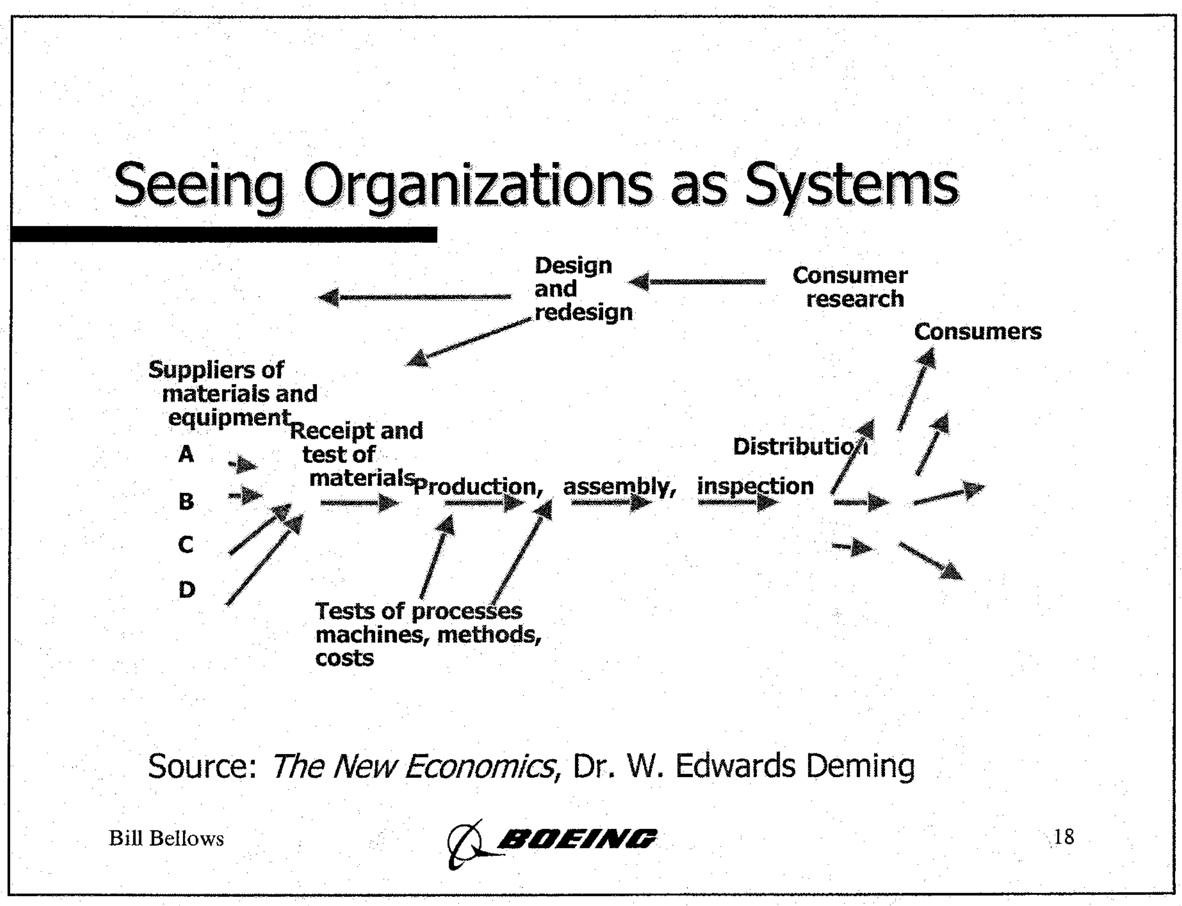

Figure 18

UTILIZATION OF THINKING

A closing reminder of the need to routinely ask questions about connections, to practice the principal of water logic. To do so is to prompt investment-thinking decisions.

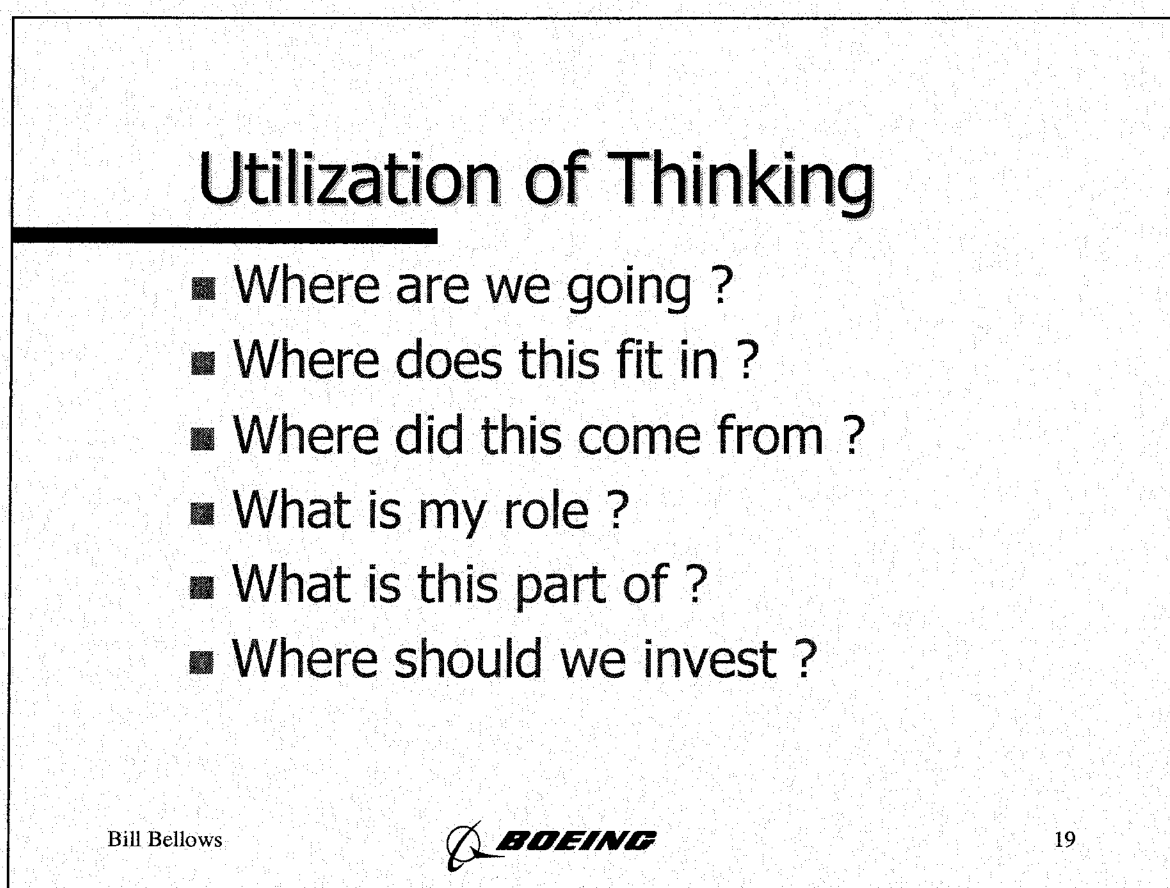

Figure 19

"BHOOMERANG KHARMA"

A reminder of what might happen when connections are not anticipated, as when one acts to focus on the parts and underestimate inevitable connections.

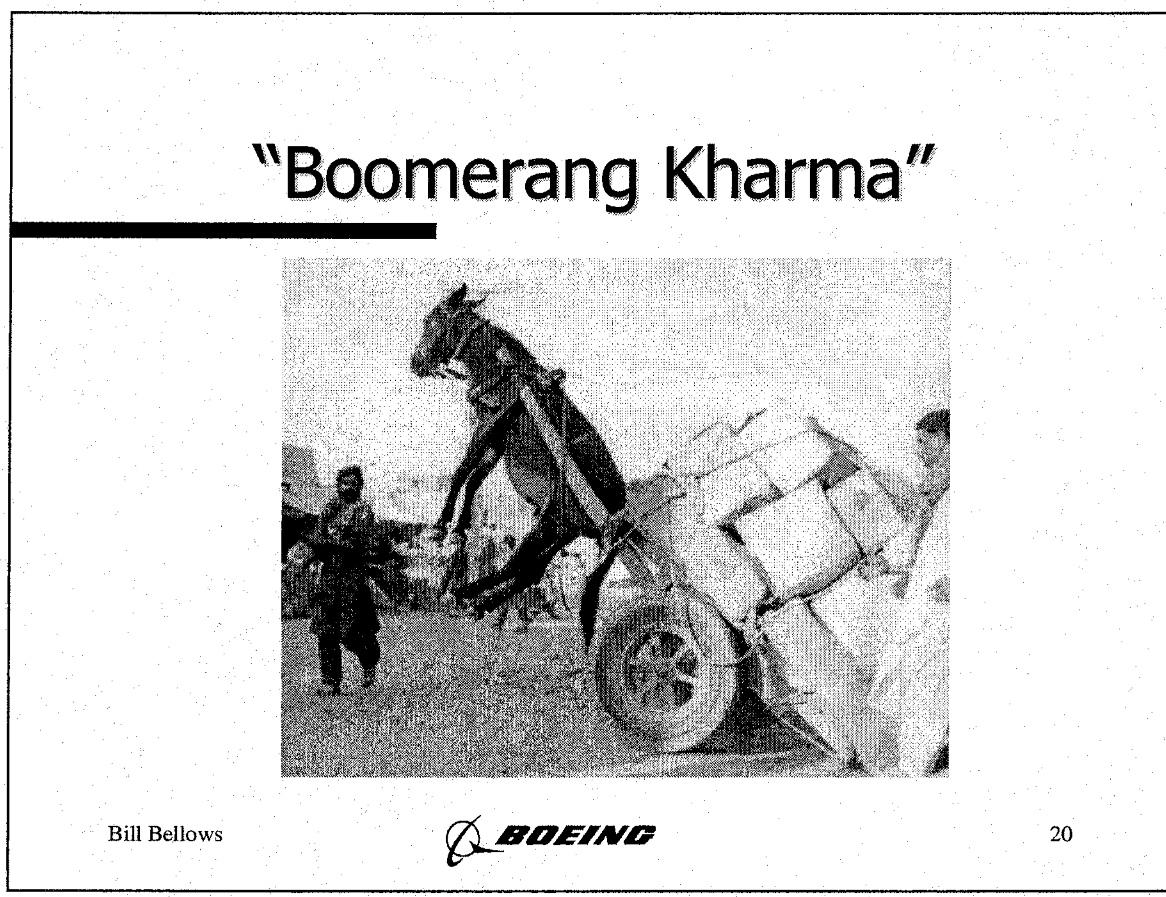

Figure 20

THE ROLE OF BETTER THINKING

In keeping with the theme of water logic, I offer a theory on the role of better thinking. I believe that if we act to "increase awareness on thinking" (through education programs or mentoring activities), and then we will "change the way we behave" (when connections are better understood, the actions that trigger undesirable results will be altered). Subsequently, we will "change the way we work together" (as when we pass on to others only what we would pass on to ourselves). In turn, we will then "change the way we run the organizations" (to treat others as we would treat ourselves is to change the operation of the organization." Such behaviors will have a reinforcing effect on "increasing awareness on thinking", leading to higher and higher levels of system consciousness and "working together".

Figure 21

3-D DIFFUSION EQUATIONS

Dr. Deming's last book, The New Economics, introduced his refinements on his evolving theory of management. He termed this management theory "the system of profound knowledge", or SOPK as an acronym. This system includes four parts, all related to each other. The parts include an understanding of variation, an appreciation of systems, of psychology, and of the theory of knowledge. Deming stressed the need to connect the pieces as a system.

As a complement to the partial differential equation that governs the diffusion of heat within an object, consider the corresponding equation that would represent the diffusion model for profound knowledge (PK) within an organization. In this case, the "Q" term represents an education system that generates PK within the organization. Such an education system has been developed with The Boeing Company to foster the "better thinking" that will lead to reduced "losses to society" and better "opportunities for companies".

3-D Diffusion Equations

of Heat

$$\partial^2 T/\partial x^2 + \partial^2 T/\partial y^2 + \partial^2 T/\partial z^2 + Q'''/k = 1/\alpha \, \partial T/\partial t$$

of Profound Knowledge

$$\partial^2 PK/\partial x^2 + \partial^2 PK/\partial y^2 + \partial^2 PK/\partial z^2 + Q'''/k = 1/\alpha \, \partial PK/\partial t$$

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Figure 22

REFERENCES

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2. Taguchi, Genichi, *Introduction to Quality Engineering*, Asian Productivity Office, 1986.

3. De Bono, Edward, Water Logic, Viking Press, 1993.

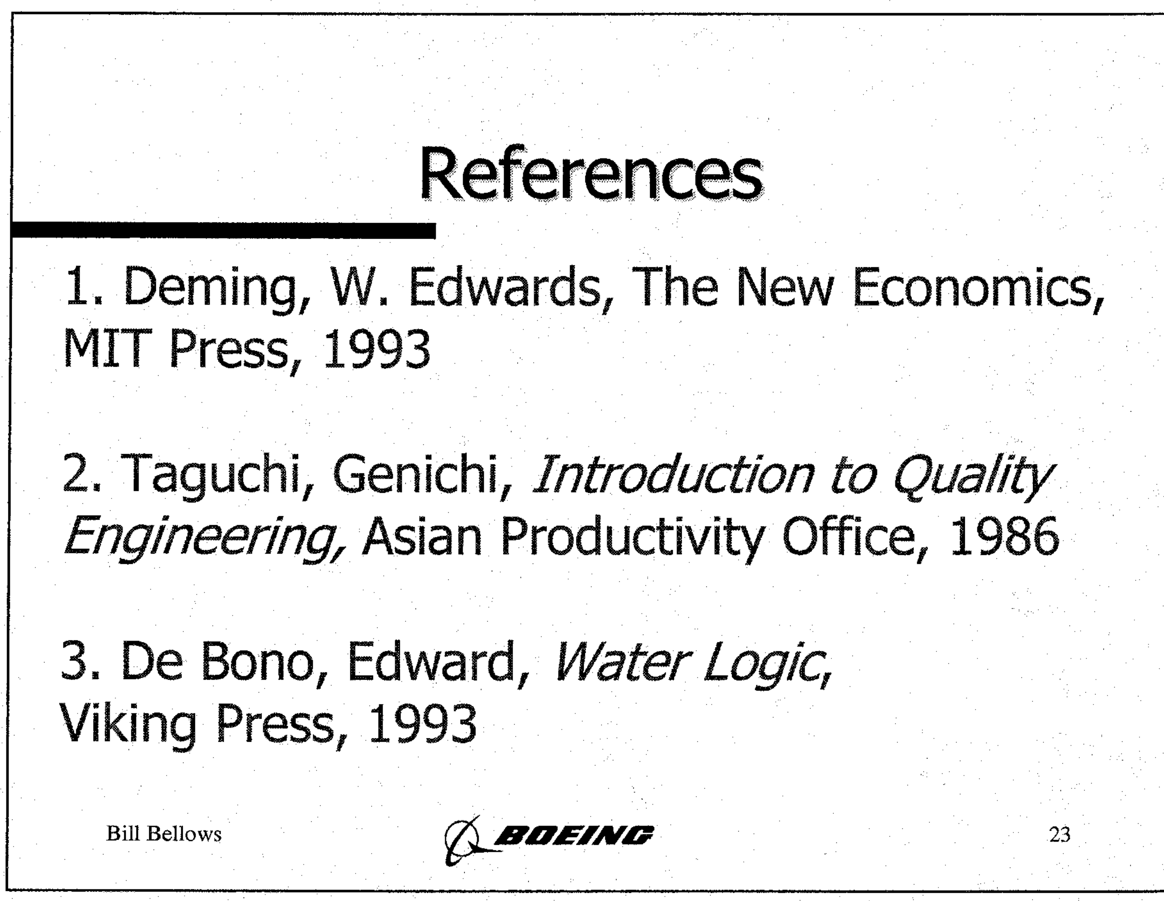


Figure 23

A Roadmap for Future NDA Applications

Gene Rogers
Boeing Space Systems Engineering
The Boeing Company
Huntington Beach, CA 92647-2099

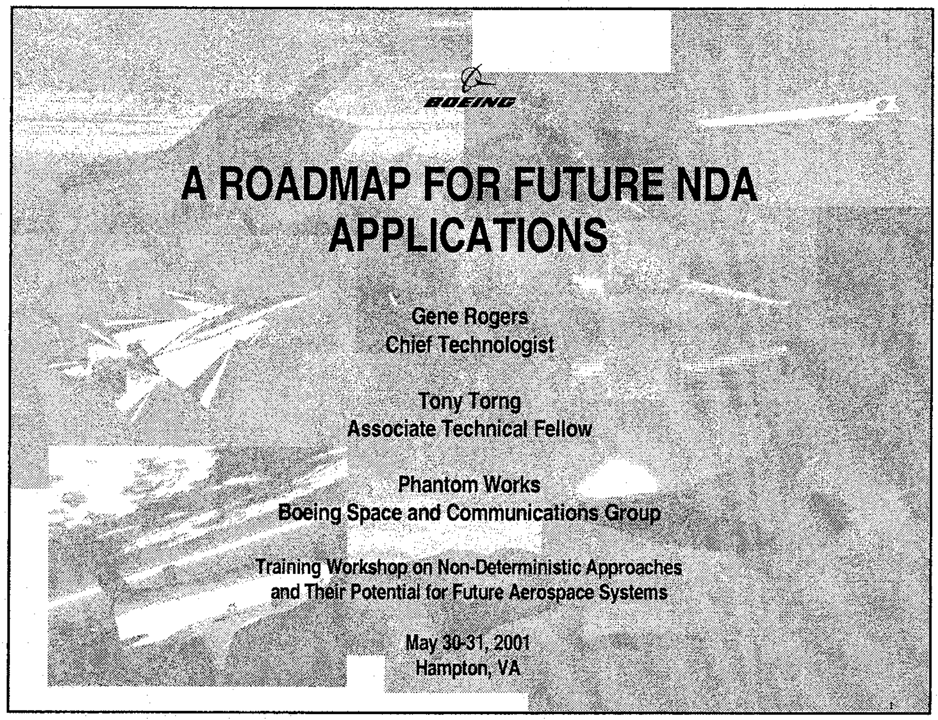


Figure 1

Credit Due to Many Contributors

- Dr. Paul Wirsching
- Dr. Suren Singhal
- Dr. Jerry Housner
- Mr. Norman R. Kuchar
- Dr. Mohammad Khalessi
- Dr. Hong-Zong Lin
- Eric Fox
- Michael Bartholomew
- Dr. David Ullman
- Mike Gulli
- Dr. Frank Chandler
- Boeing Integrated Vehicle Design System (BIVDS) Team
- Boeing Global Integrated Loads, Lines and Laws (GILLL) Team
- Boeing Rocketdyne RDCS program
- National Institute of Standards & Technology
- Science Exploratorium

2

BOEING 2

Figure 2

Outline

- Historical Model for Technical Evolution
- Current Maturity of Nondeterministic Applications
- Future Implementation Trends

3

BOEING 3

Figure 3

Historical Model for Technical Evolution

Figure 4

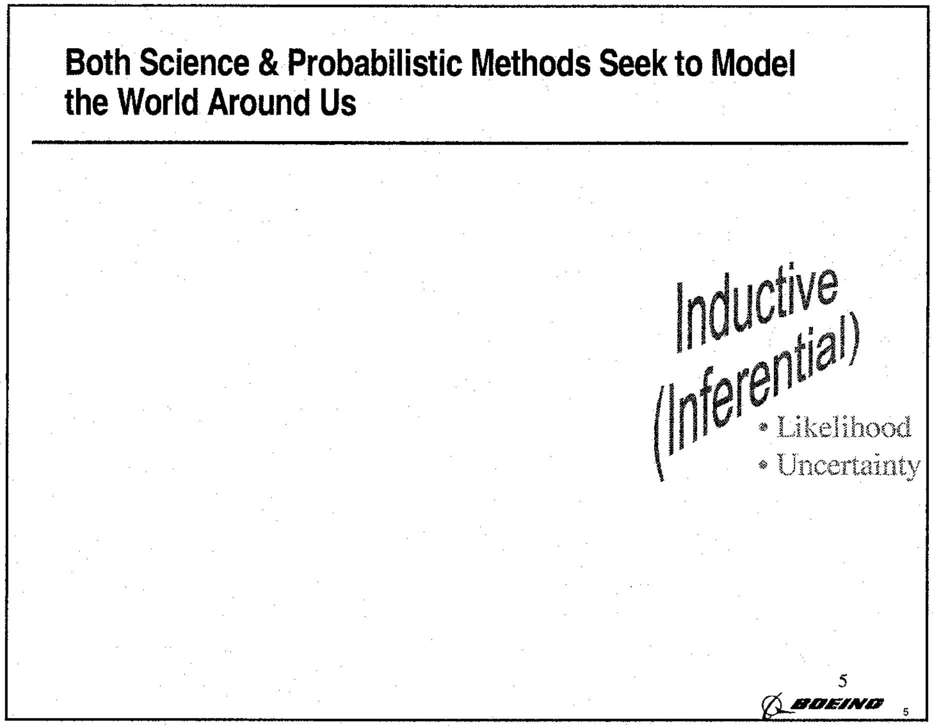


Figure 5

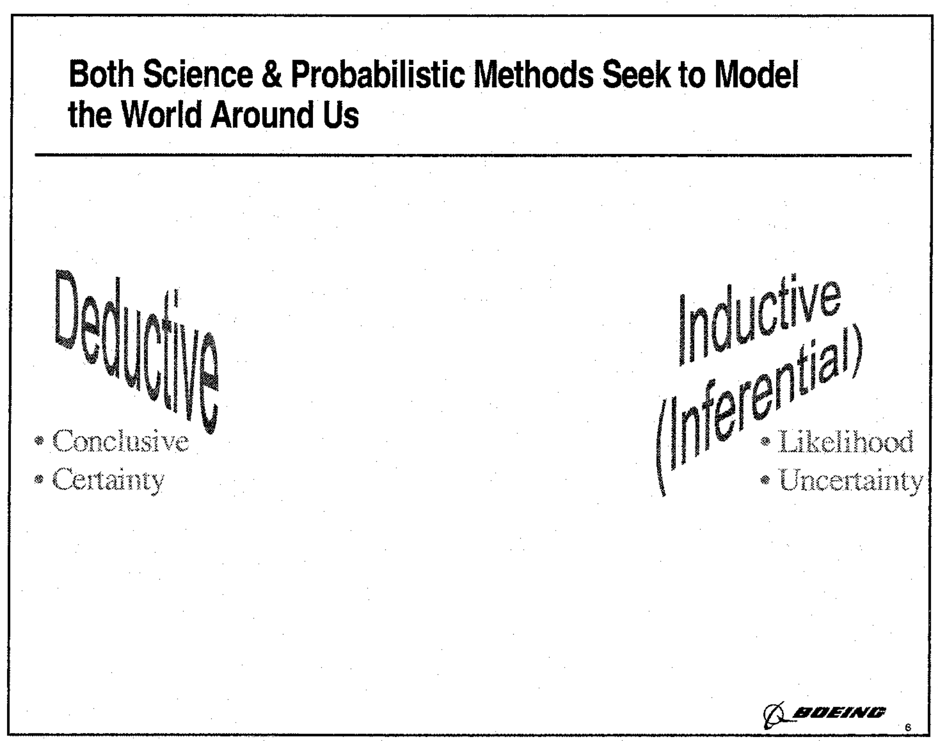


Figure 6

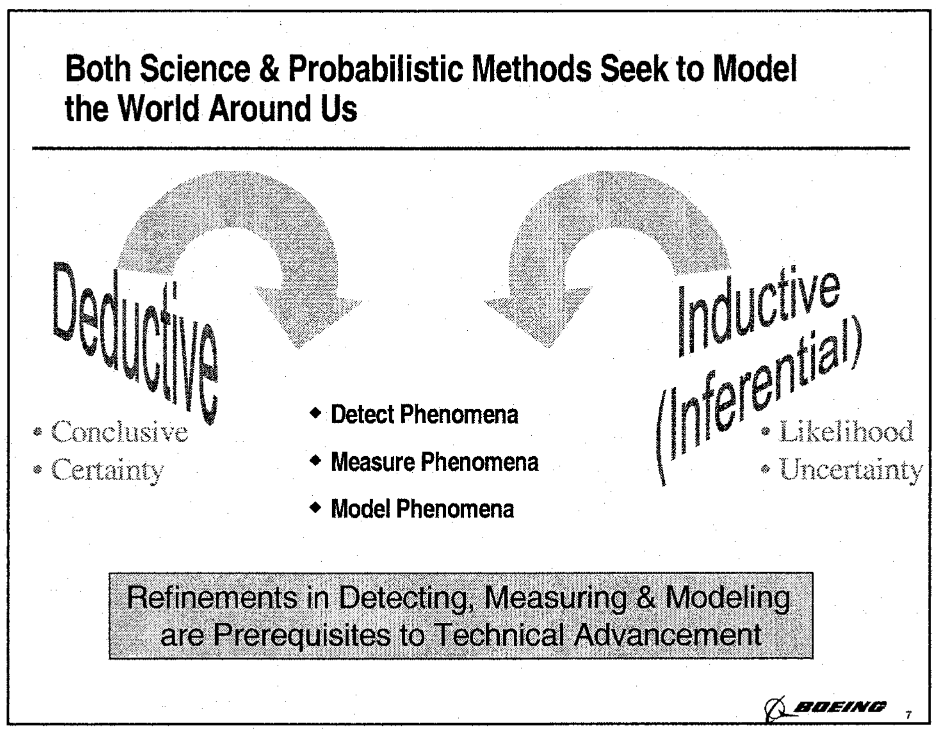


Figure 7

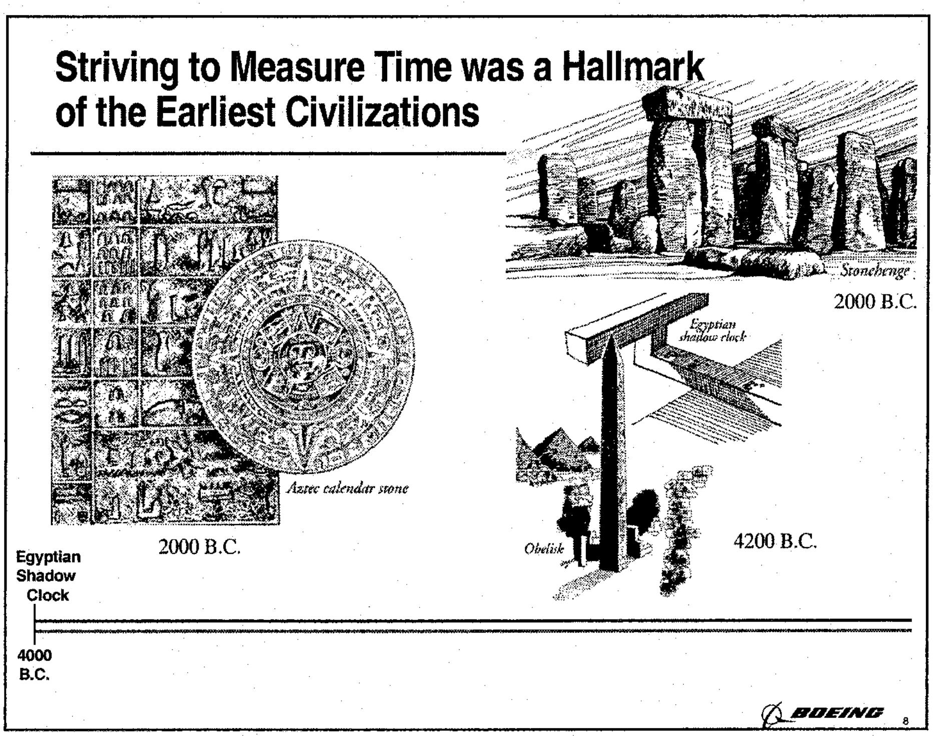


Figure 8

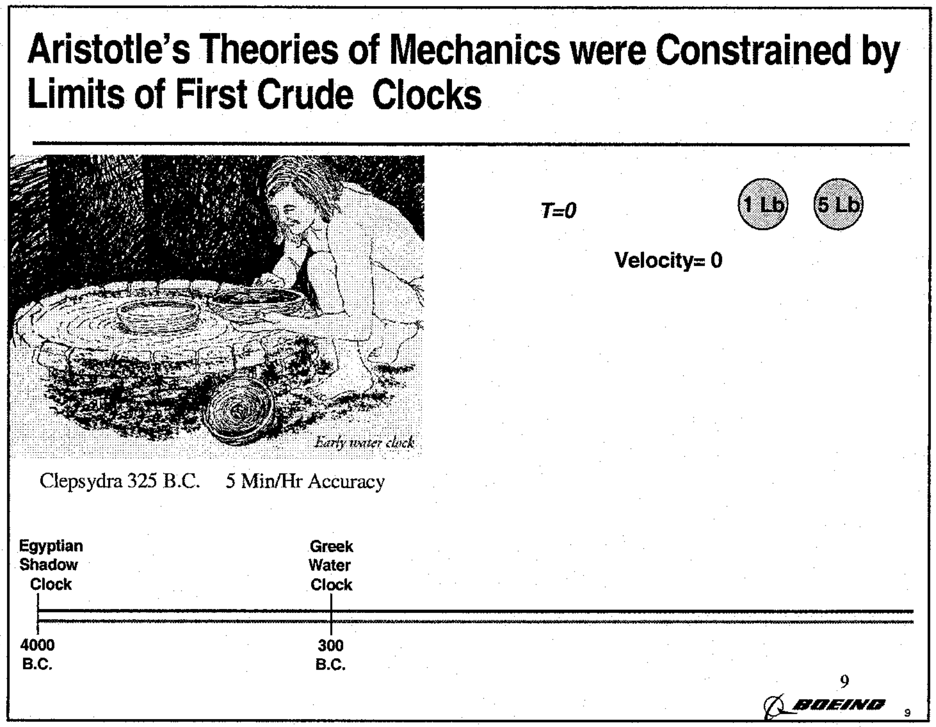


Figure 9

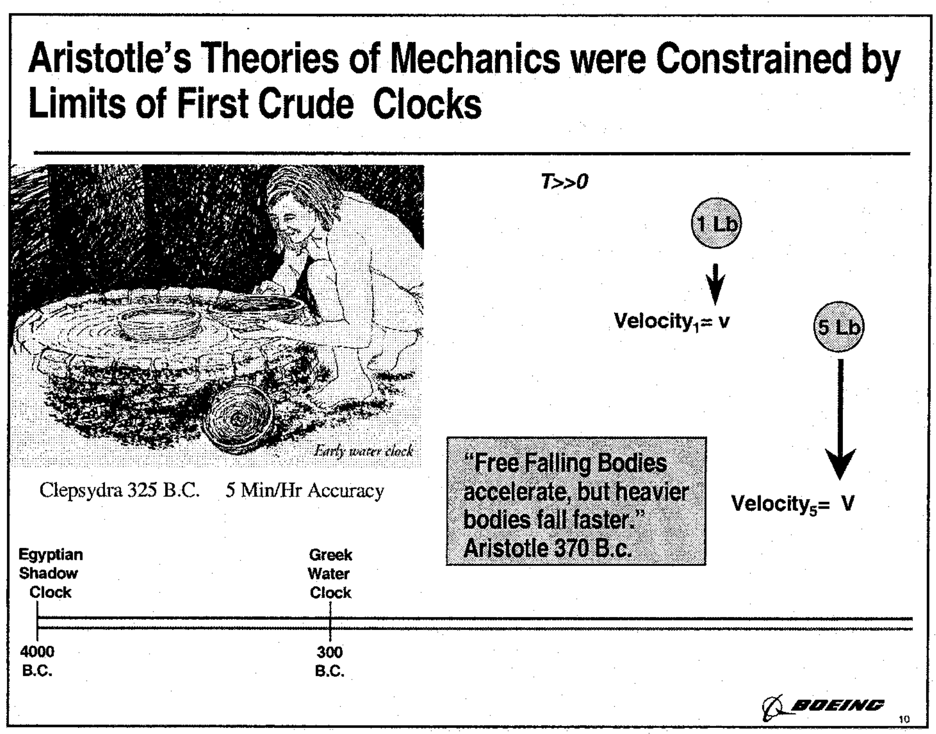


Figure 10

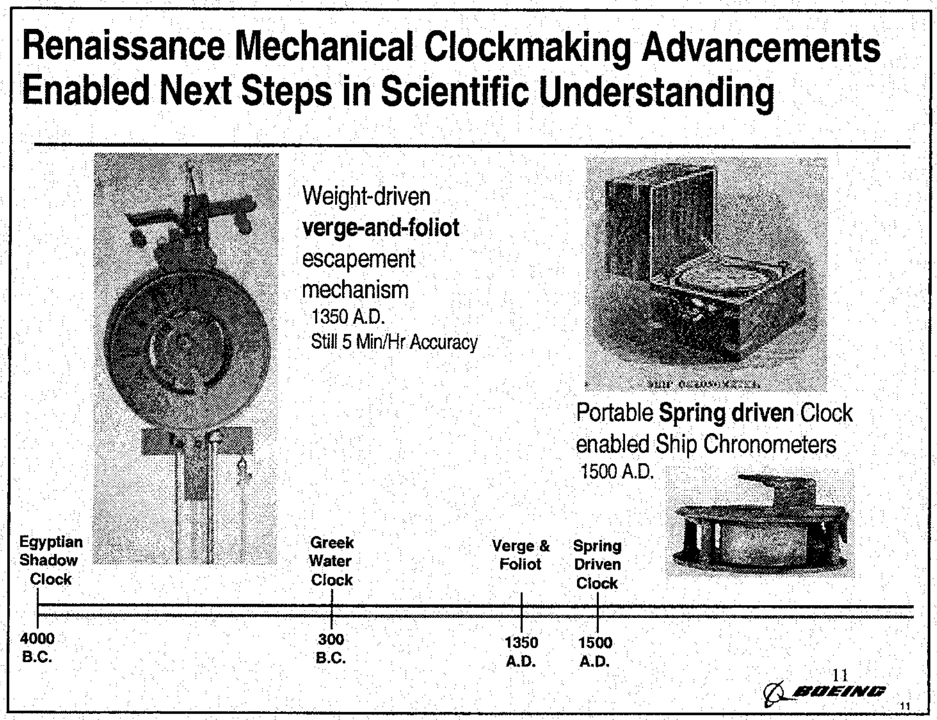


Figure 11

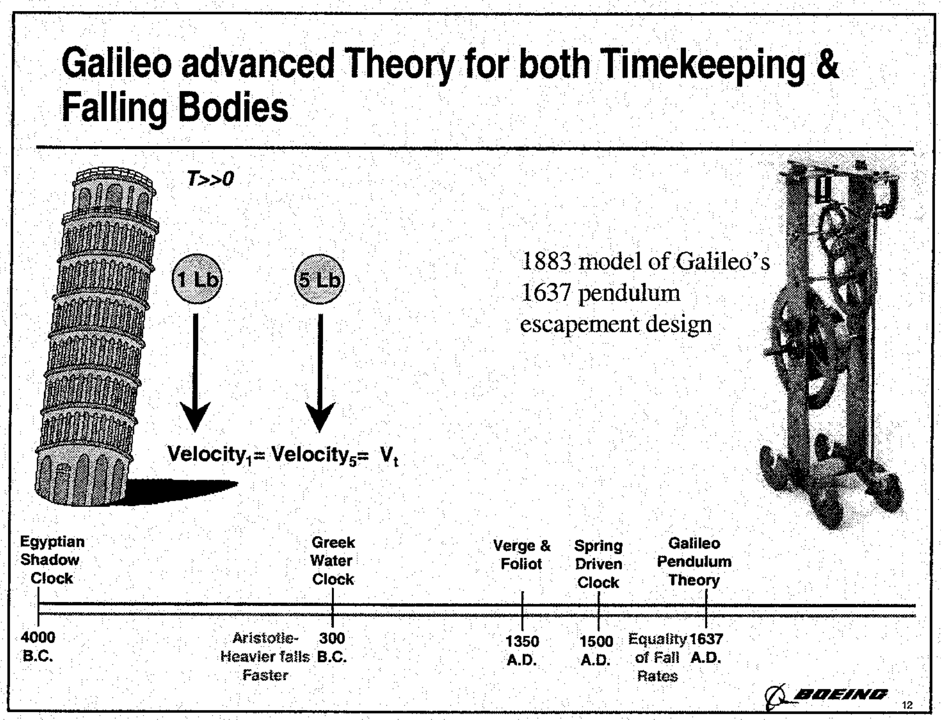


Figure 12

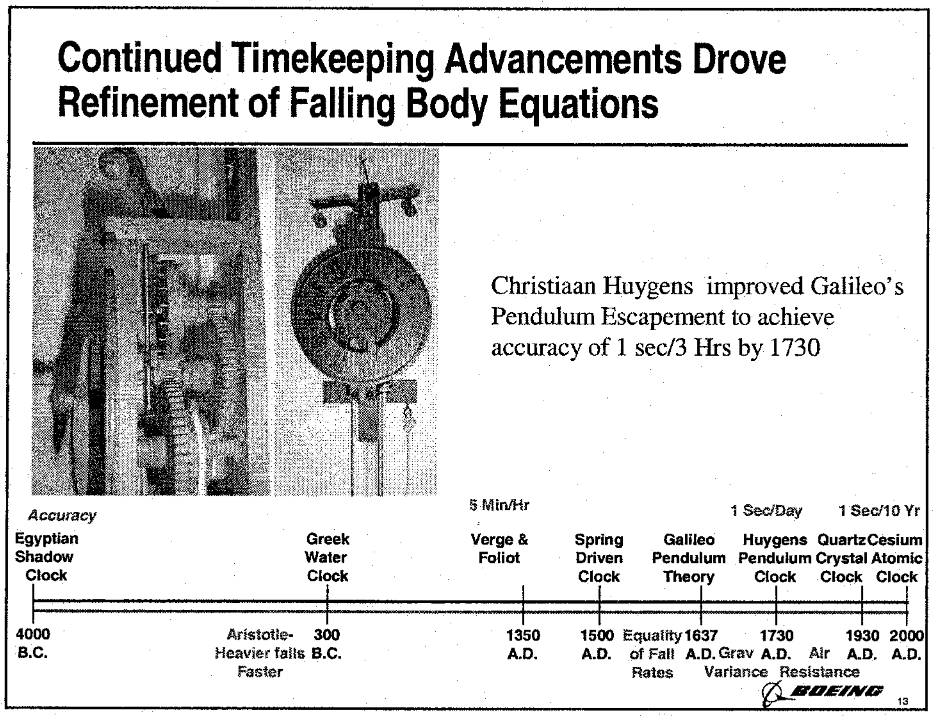


Figure 13

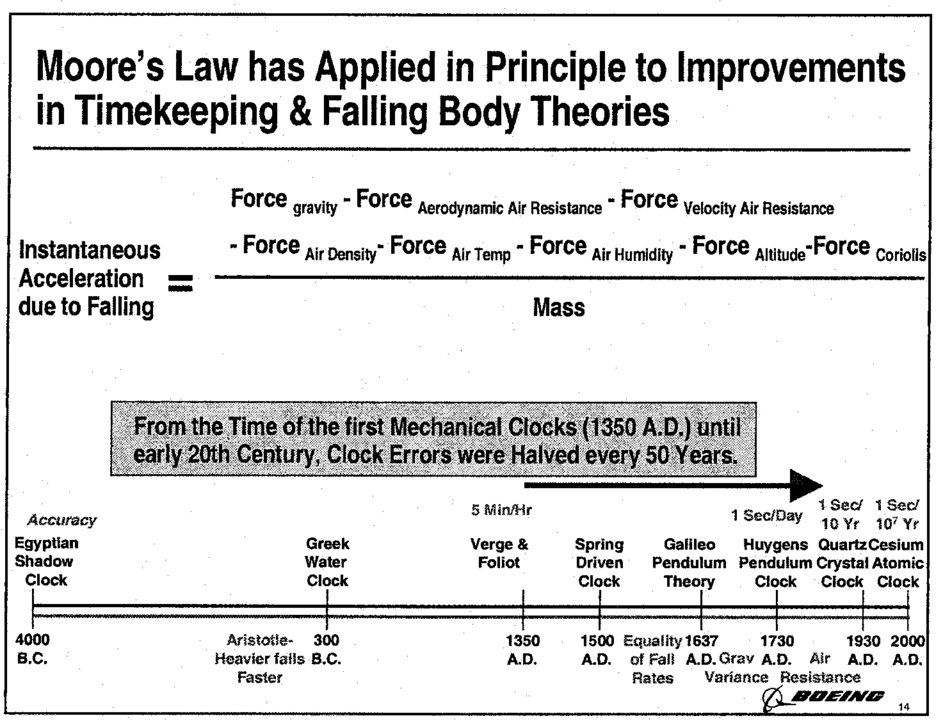


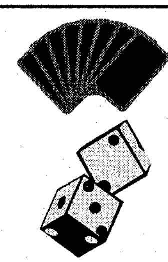
Figure 14

Current Maturity of Nondeterministic Applications

Figure 15

The Origin of Modern Probabilistic Theory Dates Back to the 17th Century

- Gambling Triggered First Applications
  - Ardent gambler, Chevalier de Mere, consulted the French mathematician Blaise Pascal (1623-1662) regarding a problem about a game of chance
- Karl Gauss (1777-1855) found applications in field theories
  - Gravity
  - Electricity
  - Magnetism.
- Pierre Laplace (1749-1827) relied on probabilistic approach in development of theories for pure mathematics



Pascal's Theory of Probability — 1650

Gauss & Laplace Applications — 1800

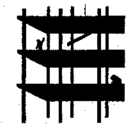
• Extracted from Prof. Paul Wirsching's "Probabilistic Design" class note

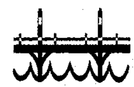
BOEING 16

Figure 16

Again... A Long Pause until the Renaissance

- Serious interest in the systematic application of probabilistic and statistical methods to structural and mechanical design did not develop until the mid-1950's.
- A paper written by A. M. Freudenthal entitled, " The Safety of Structures" appeared in the 1945 proceedings of the American Society of Civil Engineers.
- The purpose of this paper is to analyze the safety factor in engineering structures in order to establish a rational method of evaluating its magnitude.





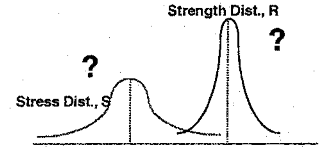
Pascal's Theory of Probability	Gauss & Laplace Applications	Safety Factor Approach
1650	1800	1950

• Extracted from Prof. Paul Wirsching's "Probabilistic Design" class note

BOEING 17

Figure 17

In 1960's, Probabilistic Design Theory Seemed Intractable Mathematically and Numerically



- Little data were available
- Modeling error was unknown
- Highly complex System structural safety analyses
- Challenges attacked in early 60's
  - Turkstra presented structural design as a problem of decision making under uncertainty and risk
  - Lind, Turkstra and Wright define the problem of rational design of a code as finding a set of best values of the loads and resistance factors
- In 1967, Cornell conceived a second moment format & demonstrated that safety index requirement led to a set of safety factors on loads and resistance.

Pascal's Theory of Probability	Gauss & Laplace Applications	Safety Factor Approach	First Structural Codes
1650	1800	1950	1960's

• Extracted from Prof. Paul Wirsching's "Probabilistic Design" class note

BOEING 18

Figure 18

Problem of Invariance Was Found for the Second Moment Format Method and Resolved in 1970's

- Second moment format based reliability design became widely accepted although a firm logical rationale was not yet demonstrated
- Ditlevsen and Lind independently discovered the problem of invariance in 1973. Cornell's index was not constant when certain simple problems were reformulated in a mechanically equivalent way.
- In 1974, Hasofer and Lind initiated the era of modern probabilistic design theory by defining a generalized safety index that is invariant to mechanical formulation.
- Several codes developed & implemented in short succession, and routine procedures documented in guideline reports
  - Comite European du Beton, 1976; Construction Industry Research and Information Association, 1977; Canadian Standards Association, 1981
- Uniform Building Code accepted Probabilistics for Civil Engineering applications

Pascal's Theory of Probability	Gauss & Laplace Applications	Safety Factor Approach	First Structural Codes	Invariance Problem Resolved
1650	1800	1950	1960's	1970's

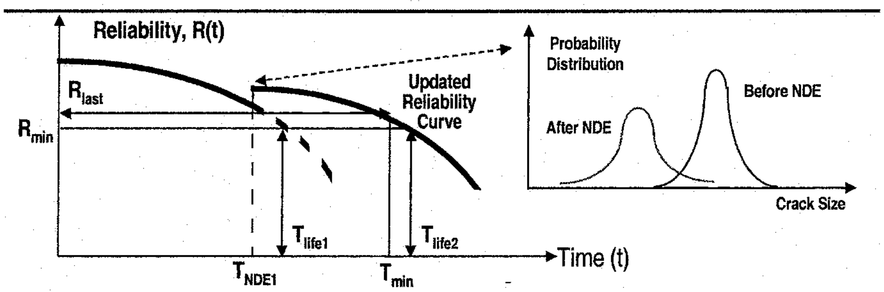
Movie Clip (MPEG)

• Extracted from Prof. Paul Wirsching's "Probabilistic Design" class note

BOEING 19

Figure 19

USAF & Dr. Jack Lincoln use Probabilistic Risk Assessment of Durability & Damage Tolerance to Recertify Fleet Lifetimes



- Design must maintain the minimum reliability level, R_{min}
- Design must exceed the minimum life expectancy, T_{min}
- Without NDE, total expected life, T_{life1} (where $T_{life1} < T_{min}$)
- With NDE, total expected life, T_{life2} (where $T_{life2} > T_{min}$)

Pascal's Theory of Probability	Gauss & Laplace Applications	Safety Factor Approach	First Structural Codes	Invariance Problem Resolved
1650	1800	1950	1960's	1970's

• Extracted from Prof. Paul Wirsching's "Probabilistic Design" class note

BOEING 20

Figure 20

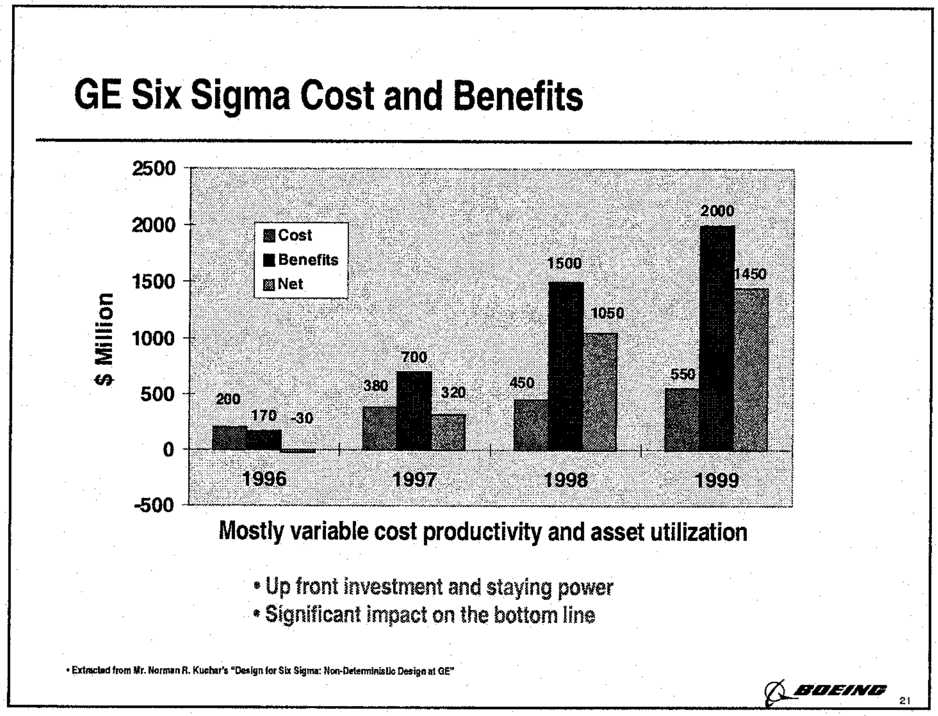


Figure 21

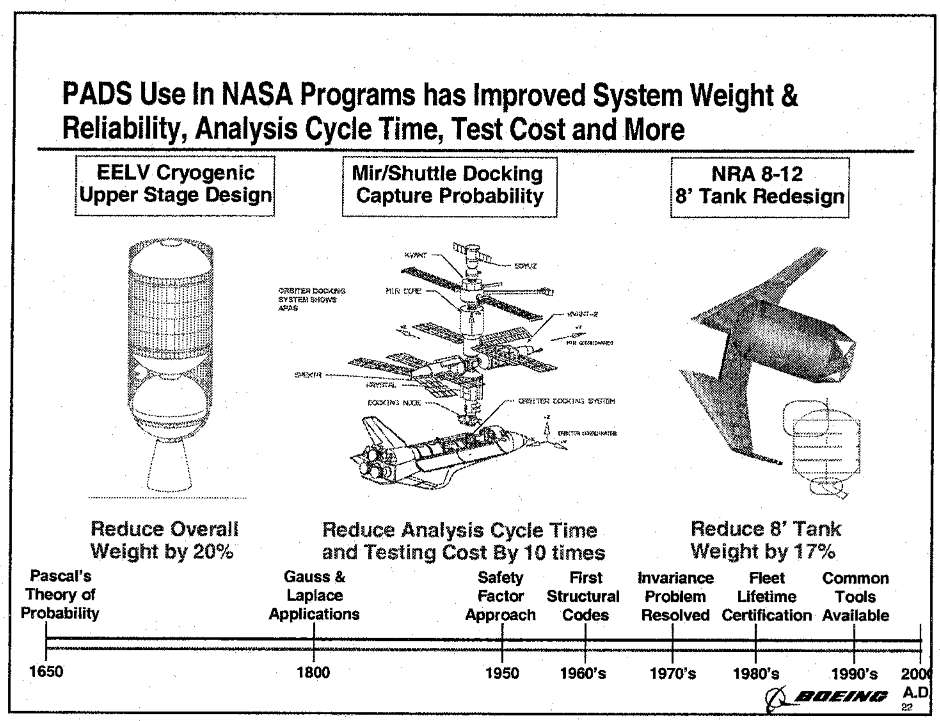


Figure 22

Future
Implementation
Trends

Figure 23

Where Do We Go From Here?
The Vision of Probabilistic Approaches

Deterministic Approach (DA) → DA-PA → Probabilistic Approach (PA)

From
- Traditional safety factor design
- Extensive design rework
- Product performance assessed by "build and test"
- Performance and producibility problems fixed after product in use
- Functionally serial product development
- Safety/Quality "tested in"
- Developed by Engineers, For use by Engineers

To
- Reliability-based design optimization
- Controlled design/random parameters
- Product performance modeled and simulated/calibrated
- Designed for robust performance and producibility
- Functionally integrated product development
- Safety/Quality "designed in"
- Developed by Engineers for use by Non-Engineers

- Reliable products are Achievable
- Revolutionize Business & Industry

• Extracted/modified from Mr. Norman R. Kuchar's "Design for Six Sigma: Non-Deterministic Design at GE"

BOEING 24

Figure 24

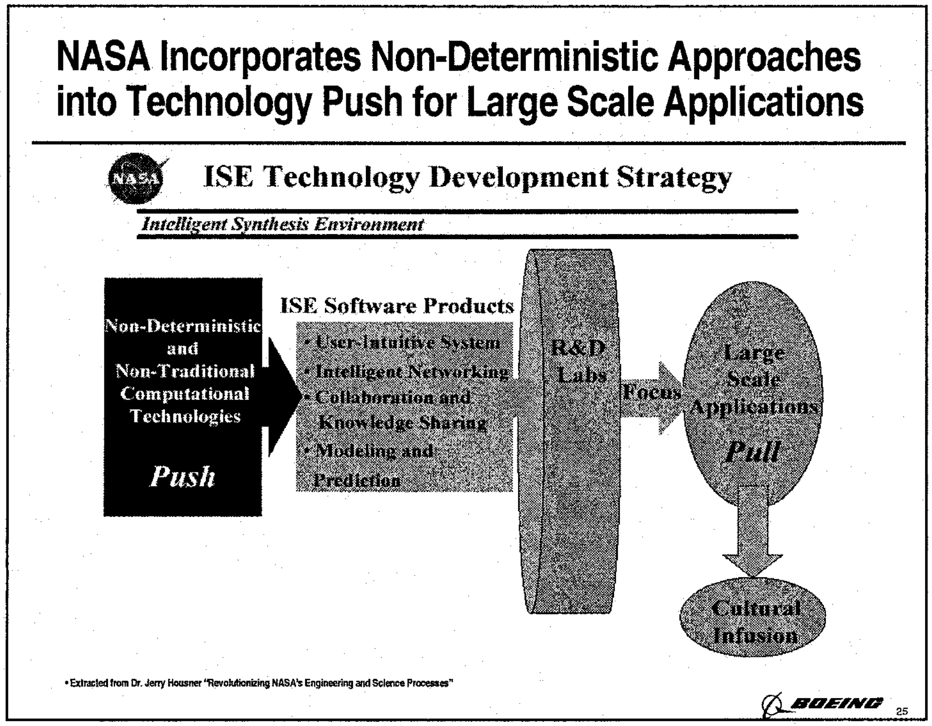


Figure 25

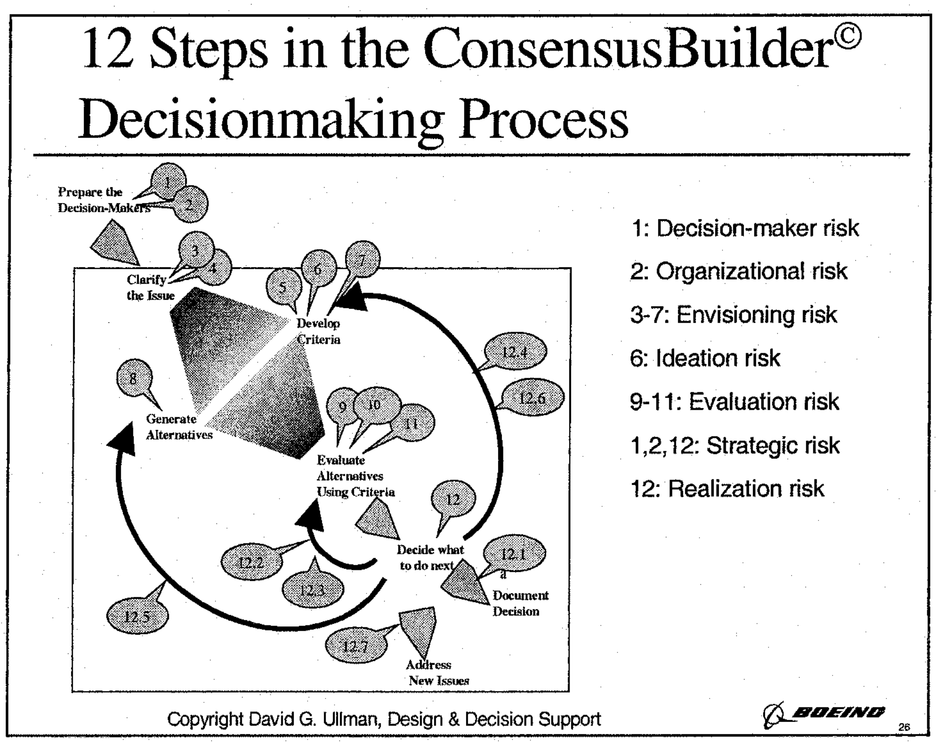


Figure 26

Opportunistic Applications are Everywhere

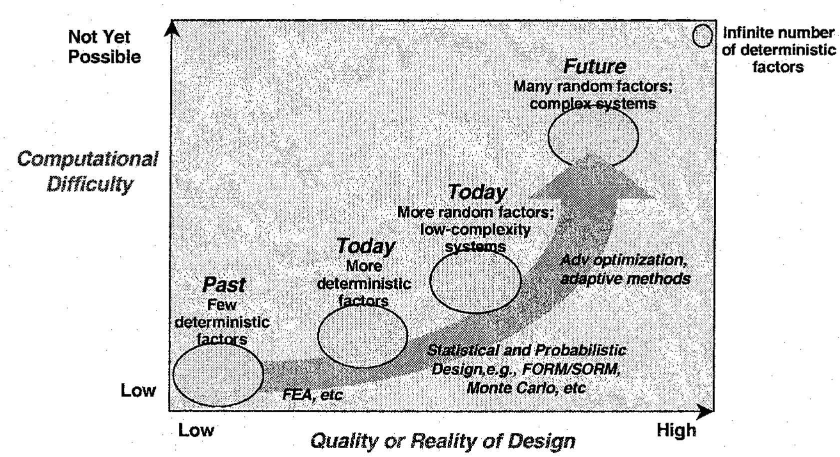
- Potential to Identify Most Probable Point and Standard Deviation is inherently useful to any business
- Technical Approaches are needed in qualitative fields to foster transition from Inference to Deduction
- Boundaries are self-imposed
- Near-term opportunities need more attention
  - Costing & Pricing
  - Scheduling
  - Insurance
  - Design of Mission, Operations & Manufacturing Flows
  - Law

Focus on Structures Distracts from Proliferating Nondeterministic Methods across All Industries & Businesses

27

Figure 27

Success of Probabilistic Approach Requires Practitioners to Push the Application Envelope



•Extracted/modified from Mr. Norman R. Kuchar's "Design for Six Sigma: Non-Deterministic Design at GE"

28

Figure 28

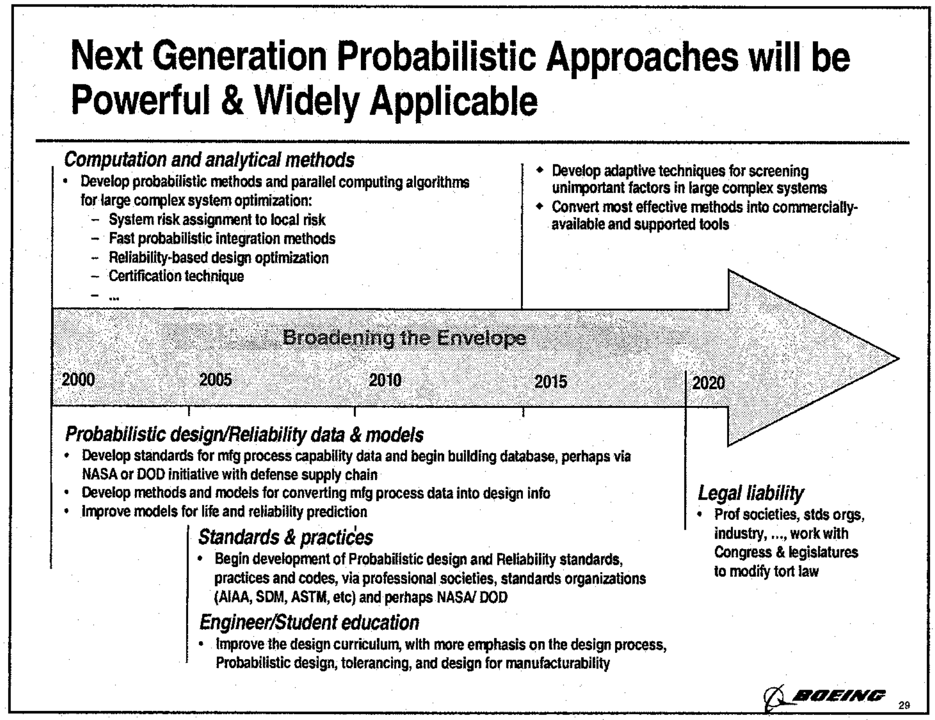


Figure 29

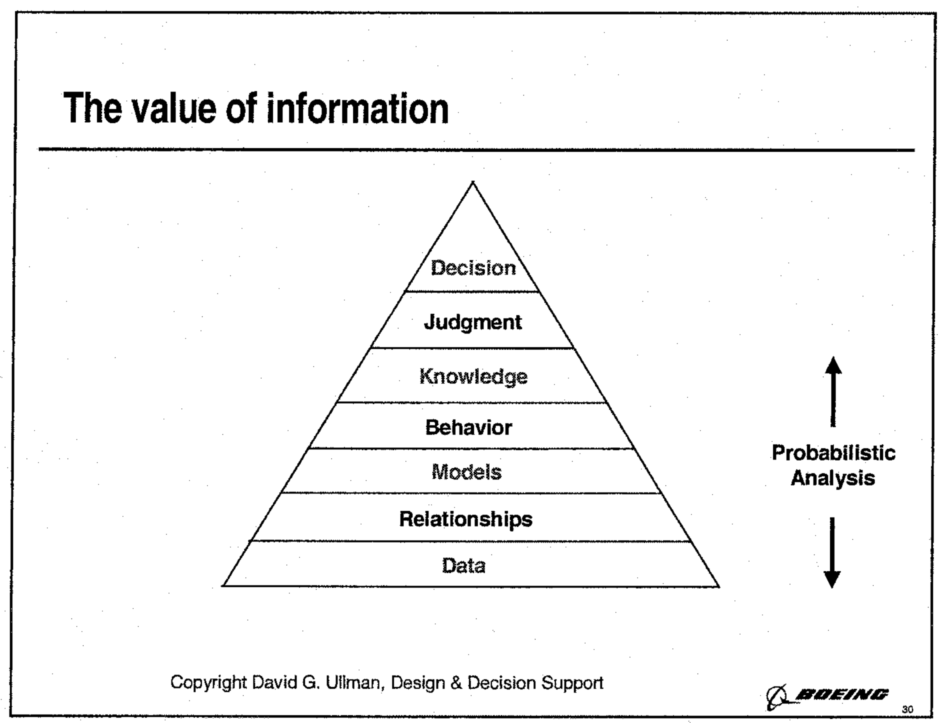


Figure 30

Ultimately, Probabilistic Methods are Aids to Decisionmaking by Management

- Goes directly to the Challenge of Modeling the World that We see around Us
- Facilitates the Historical Transition from Inferential to Deductive Assessments
- Models transform raw Data into Knowledge to enable Decisions
- Technical Methods are being infused Today into Management and other inherently Subjective fields
- Managers are crying out for reliable Decision Aids
- Rate of Transition & Successful Use of Probabilistic Methods will be determined by Developers of the methods

CARPE DEUM- Seize the Moment

BOEING 31

Figure 31

Summary of NDA Activities of Professional Societies

Dr. Suren N. Singhal
QSS Group Inc.
NASA Glenn Research Center
Cleveland, OH 44149

SUMMARY OF NDA ACTIVITIES OF PROFESSIONAL SOCIETIES

This presentation summarizes activities of some professional societies in the area of non-deterministic approaches (NDA). Major NDA activities of SAE (Society of Mobility Engineering) and AIAA (American Institute of Aeronautics & Astronautics) are discussed. There are on-going NDA activities in other societies such as ASME (American Society of Mechanical Engineering) and ASCE (American Society of Civil Engineering), which are not covered in this presentation. The presentation demonstrates that engineers can achieve full potential as contributors in professional engineering organizations.

The SAE G-11 Probabilistic Methods Committee provides a good source of information wrt various technological, applications, communications, education, training, and related issues for any one to make use of them.

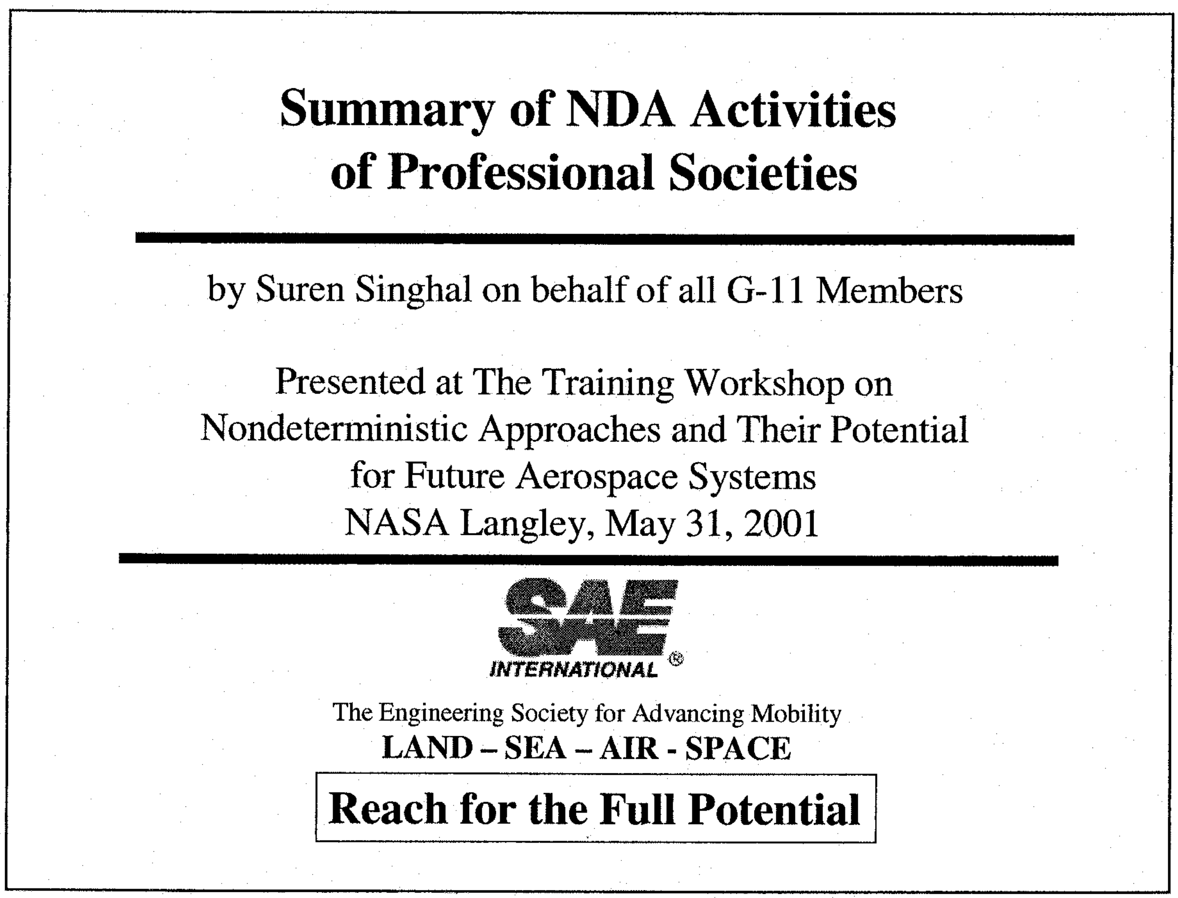


Figure 1

OUTLINE

Non-deterministic approaches are introduced in the context that led to the initiation of the SAE & AIAA activities about a decade ago. The SAE, AIAA, and other non-profit NDA activities are then discussed. Conclusions & recommendations for the engineering community are presented.

Outline

- Introduction
- SAE Activities
- AIAA Activities
- Other Professional Activities
- Conclusions & Recommendations

Figure 2

INTRODUCTION

The critical issue in todays fast moving engineering world is delineated along with a proven solution. The accompanying challenges are highlighted. The solution requires a systems perspective to fully address the issues of today's engineering community. All this is linked with the role of professional societies in addressing such issues, solutions, and challenges for the benefit of all.

Introduction

- Issue, Proven Solution, Challenges
- Examples
- Systems Perspectives
- Role of Professional Societies

Professional Societies Serving the Community Needs

Figure 3

ISSUE AND PROVEN SOLUTION

Many countries are at the leading edge of technology while the U.S. national budget for cultivating the frontier technologies keeps getting tighter, demanding more-than-ever efficient return on investment. New innovative ways must be adopted if they lead to real and measurable cost reduction and efficiency improvements. Perceptions alone will not suffice. Some form of NDA/probabilistic engineering has been proven to result in significant real and measured savings. The time is ripe for prudent implementation of such technologies for the benefit of all.

Issue

Global competition and the state of U.S. national budget mandate the need for new innovative ways of increasing efficiency with **real and measurable cost reduction.**

Proven Solution

Some form of probabilistic engineering is currently being used by some U.S. corporations, resulting in billions of dollars of **real and measured savings.**

A sample use of probabilistic engineering by U.S. Air Force has demonstrated savings of millions of dollars.

THE TIME IS RIGHT FOR PROBABILISTIC ENGINEERING

Figure 4

CHALLENGES

Like any new innovation, there are multiple challenges that must be addressed heads-on, rather than ignoring them, so as to enable successful applications of probabilistic engineering. With the phenomenal success of engineering innovations designed by deterministic approach, it is not an easy task to convince experts to adapt to non-deterministic approaches. And then there must be documented proofs that such approaches do offer competitive advantage. Further, there is a need for adequate training, the requisite tools, and certification guidelines. And then there are cultural and legal barriers, which are being addressed by the SAE activities. The bottom line is such a paradigm shift is easier said than adopted.

Challenges

- Today's Safety Factor Approach
- Show me the proof
- Training, tools, certification
- Barriers, legal issues

Paradigm shift is easier said than adopted

Figure 5

EXAMPLES OF PROBABILISTIC ENGINEERING WITH DEMONSTRATED COST SAVINGS

The examples of probabilistic engineering with demonstrated savings include those by major organizations such as by Northrop Grumman for fighter wing, Lockheed Martin for bird strike, P&W for aircraft cooling, Boeing (previously Rockwell) for Space Shuttle Docking Module, and applications of Six Sigma at Motorola, Allied Signal, and GE. The probabilistic engineering leads to realistic savings, generally with an order of magnitude cost to benefit payoff.

EXAMPLES OF PROBABILISTIC ENGINEERING WITH DEMONSTRATED COST SAVINGS

- Fighter wing --- REDUCED WEIGHT BY 15% (Northrop-Grumman)
- Bird strike on aircraft engine ---SAVED LIVES (Lockheed-Martin)
- Aircraft cooling duct fabrication --- SAVED \$500K (P&W)
- Space Shuttle docking module --- REDUCED TESTING COST FROM \$500K TO \$50K (Boeing-Rockwell)
- PE-based Design for Six Sigma --- MOTOROLA SAVED \$11B and GE ON THE WAY TO SAVE \$8B

Probabilistic engineering is for real with proven order of magnitude savings. Expect > 1 to 10 cost to benefit payoff!!

backup

Figure 6

SYSTEMS PERSPECTIVE

The uncertainties are naturally present in every aspect of engineering life cycle from defining mission-reliable requirements which must lead to an innovative concept to risk-averse design resulting in a competitive product that a customer will value for performance over cost and use the product safely with economical maintenance and final retirement with overall greater than one return on investment. This is the overall systems perspective that weaves uncertainties in each step of any system's life cycle that would result in profitable ventures

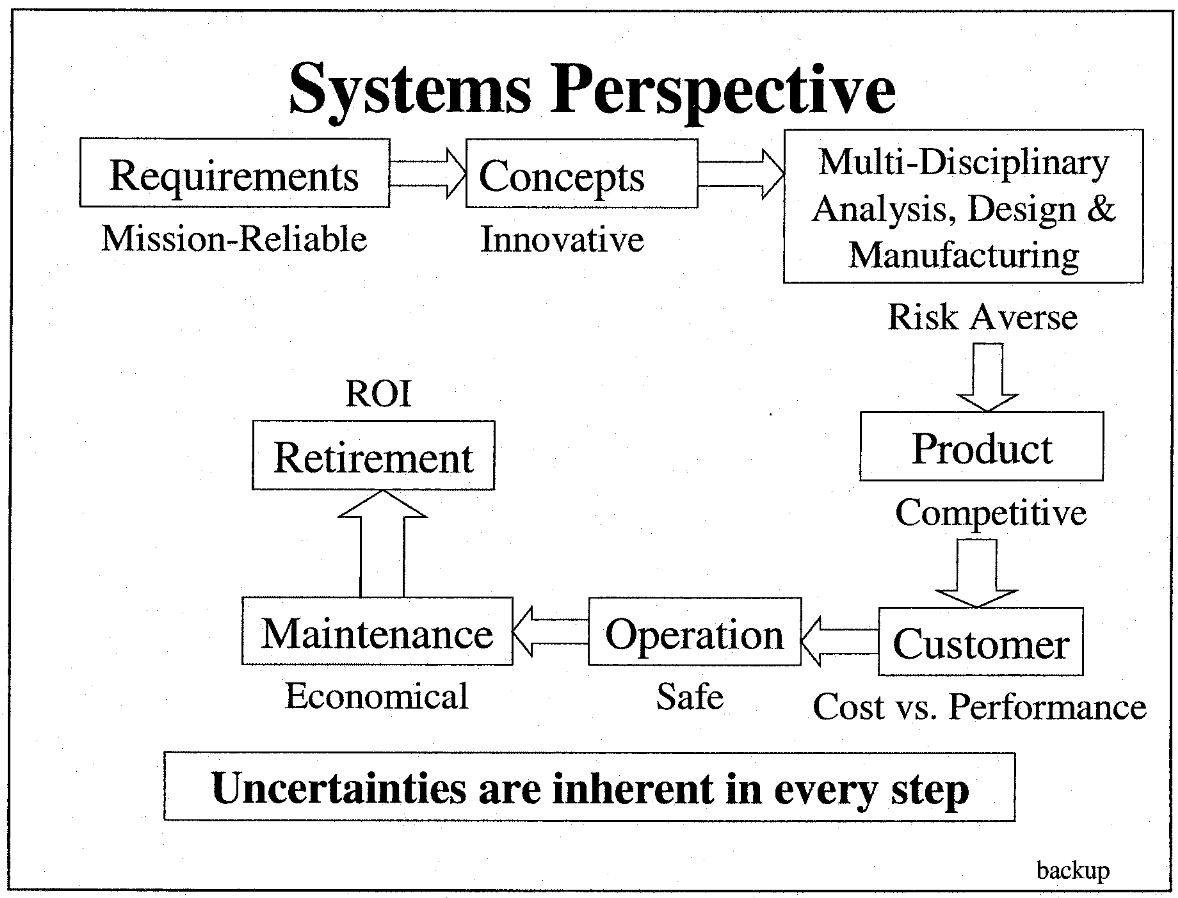


Figure 7

ROLE OF PROFESSIONAL SOCIETIES

The professional societies can and must act as a catalyst in bring together new ideas, technologies, and people. The professional societies can play a pivotal role in bringing to limelight worthwhile futuristic innovations faster than they otherwise would. These societies must help engineering community make aware of such new technologies, help enhance their understanding of convincing intricacies, and be a clearinghouse of much-needed training, tools, and experts. The professional societies can accelerate implementation of futuristic technologies, starting from small pilot projects conducted in a cooperative multi-organizational environment.

Role of Professional Societies

- **Awareness**
- **Understanding**
- **Resources**
  - ***Tools**
  - ***Training**
  - ***Experts**
- **Implementation**

Professional societies can be the catalyst in bringing people & new ideas together

Figure 8

SAE G-11 ACTIVITIES

The SAE G-11 Division activities will be discussed in three parts: (1) the Reliability, Maintainability, Supportability, and Logistics (RMSL) Division, (2) the Probabilistic Methods (PM) Committee, and (3) the Probabilistic Methods Leadership Council (PMLC). The website for details on these activities is provided below.

SAE G-11 Activities

- RMSL Division
- Probabilistic Methods (PM) Committee
- PM Leadership Council

SAE G-11 Web site:
http://forums.sae.org/access/dispatch.cgi/TEAG11PM_pf

Figure 9

WHY ARE WE HERE?

The SAE G-11 RMSL Division gathers together semiannually to serve the needs of the land, sea, air, and space engineering community. By understanding the needs and working on need-based projects, the SAE members deliver information, standards, education, and training.

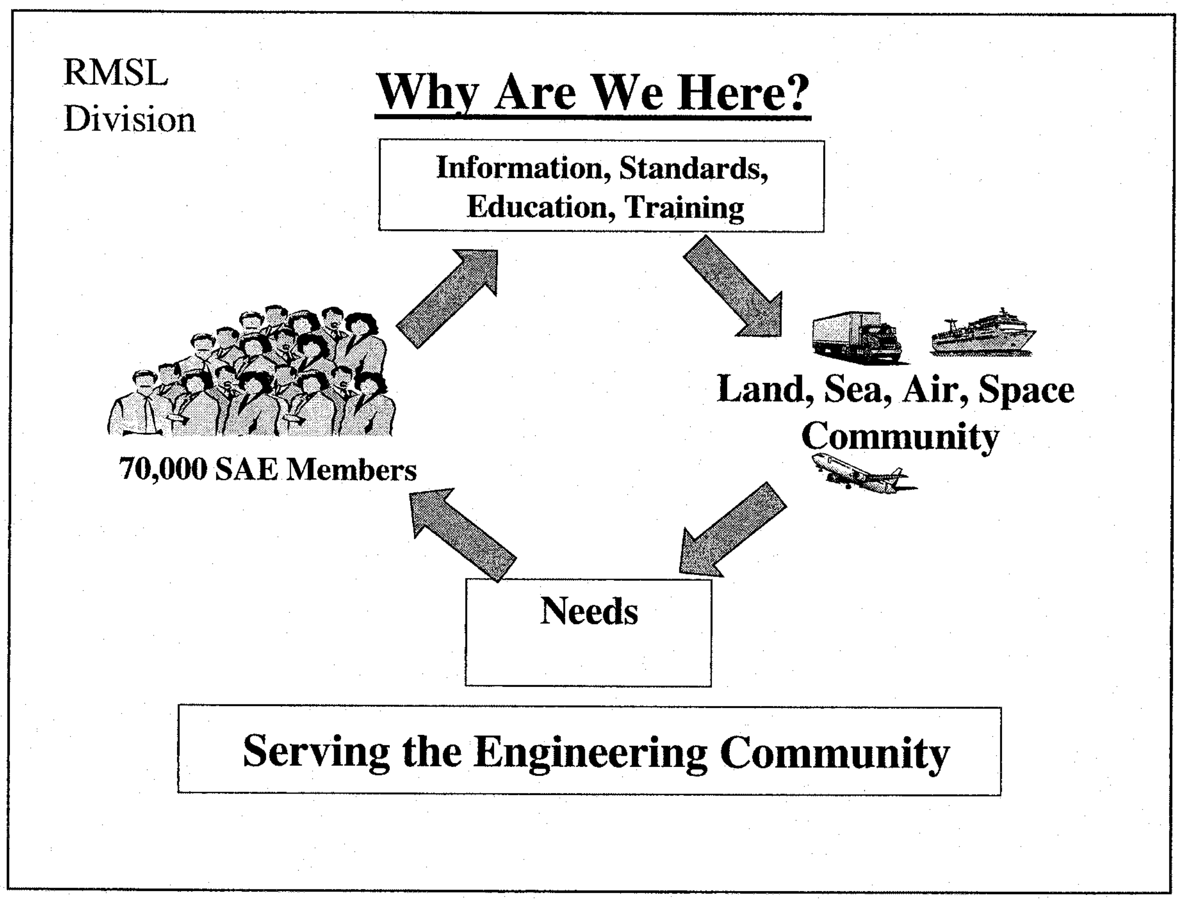


Figure 10

WHY ARE WE HERE?

This chart summarizes the benefits of attending the G-11 meetings including: (1) face-to-face interaction with peers, (2) an opportunity to measure how an individual organization stack up against the state-of-the-art, (3) the best engineering practices, (4) technology exchange, (5) networking, (6) list of needed information and resources such as meetings, seminars, etc., and (7) a venue for partnering with others. The G-11 Division hopes to always provide benefits outweighing the expense of attending the meeting.

RMSL
Division

Why Are We Here?

- Industry, govt., academia face-to-face
- How does your organization compare?
- What are the best practices?
- Technology interchange and networking
- Access to information and resources
- Partnership with some of the best in the business

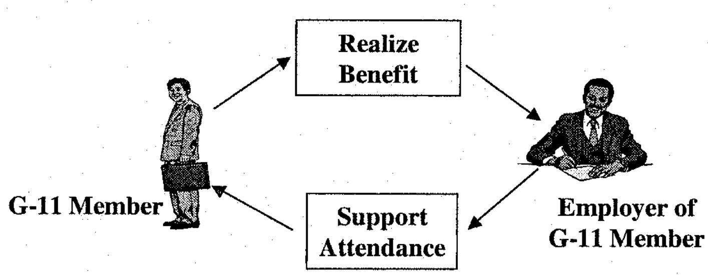


Figure 11

HOW DO WE WORK?

This chart depicts the real workings of the G-11 Division. We try to understand the generic needs of organizations at large. We develop projects based on these needs and deliver the results to the customer. Of course, the individuals and organizations attending the meeting tend to benefit more as their needs are brought out in the open discussions at our semiannual meetings.

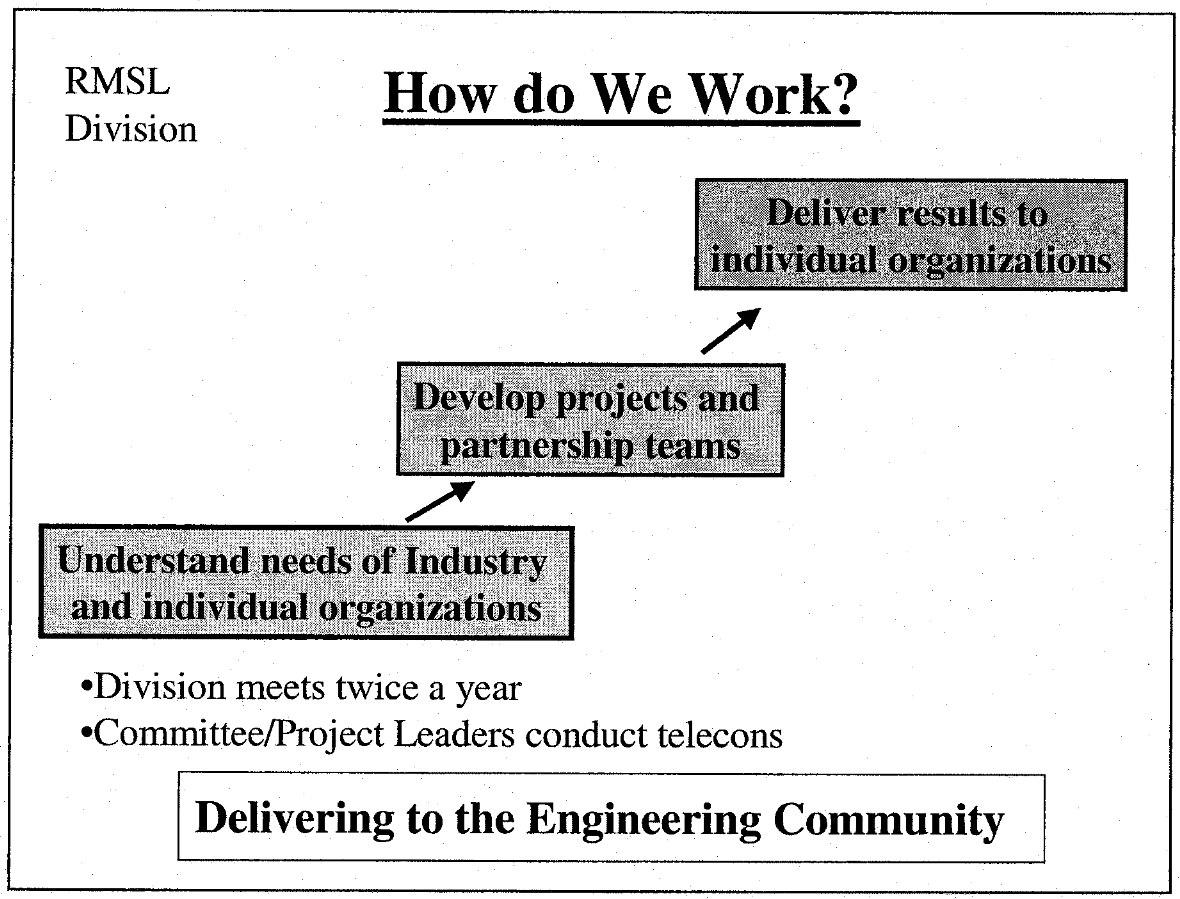


Figure 12

ORGANIZATION

This chart shows the width and depth in terms of the projects and people involved in our organization, which remains dynamic and flexible, based on changing needs of the engineering community that it serves.

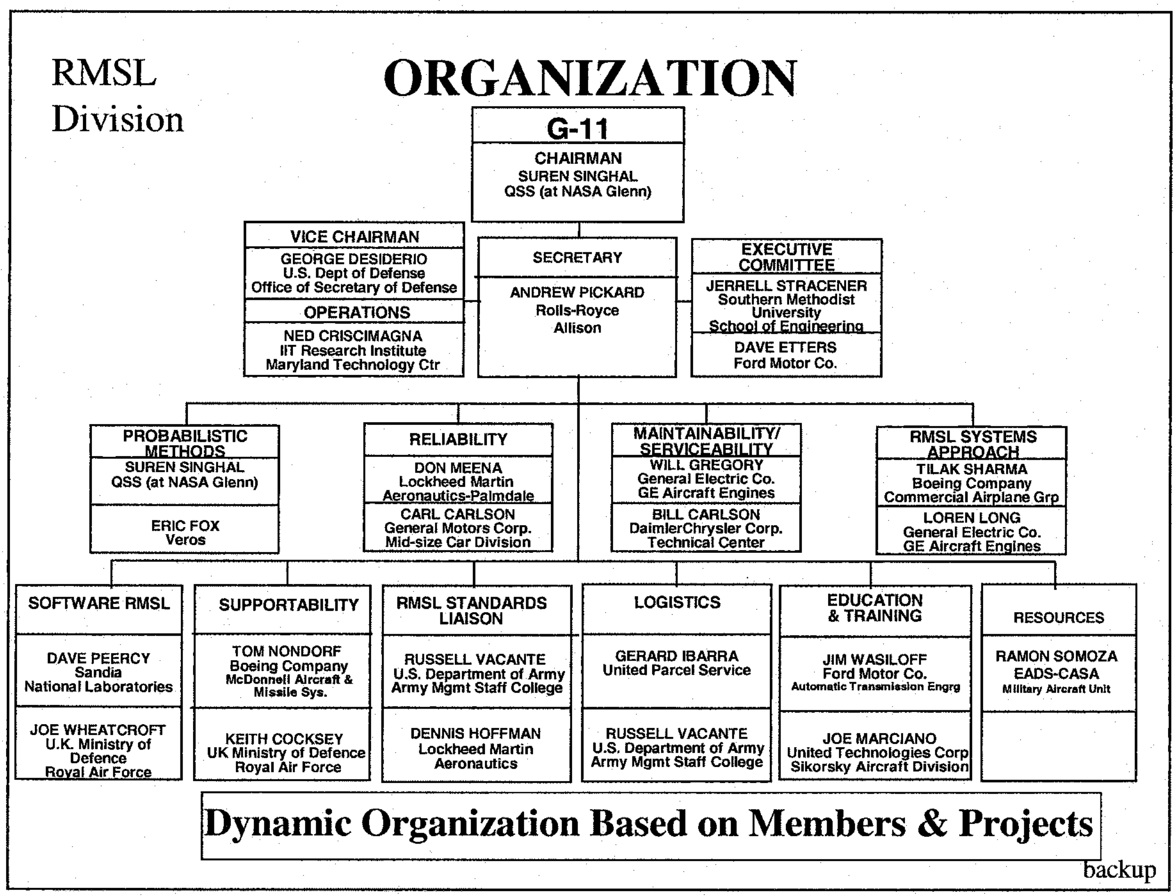


Figure 13

WHAT HAVE WE DONE SO FAR?

The G-11 Division has published documents with recommendations, guidelines, and standards. It has conducted workshops as needed by the community. The Division meetings have led to significant industry, government, and academia interaction. The Division is dedicated to making a difference.

RMSL
Division

What Have We Done So Far?

- Published resource documents, information reports, standards and guidelines on RMSL & PM
- Conducted Workshops
- Facilitated significant industry, government and academia interaction
- ------------------

The G-11 Members Keep Making a Difference

Figure 14

PRELIMINARY LIST OF PUBLICATIONS ISSUED
(AVAILABLE FROM SAE – 724-776-4841)

A sample list of G-11 publications is attached here.

RMSL Division **Preliminary List of Publications Issued (Available from SAE – 724-776-4841)**

	Title	Publ.	Product Code	Sponsor
1	"Evaluation Criteria for Reliability Centered Maintenance (RCM) Processes"	8/99	JA1011_199908	TEAG11SL (Chair: D. Netherton)
2	"Software Support Concept"	6/99	JA1006_199906	TEAG11 (Chair: D. Peercy)
3	"Reliability Program Standard Implementation Guide"	3/99	JA1000/1-199903	TEAG11R (Chair: D. Elters)
4	"Perceptions and Limitations Inhibiting the Application of Probabilistic Methods"	12/98	AIR5086	TEAG11PM (Chair: C. Pomfret)
5	"Software Reliability Program Standard"	7/98	JA1002_199807	TEAG11SW (Chair: D. Peercy)
6	"Software Supportability Program Implementation Guide"	7/98	JA1004_199807	TEAG11SW (Chair: D. Peercy)
7	"Reliability Program Standard"	6/98	JA1000-199806	TEAG11R (Chair: D. Elters)
8	Probabilistic methods, A Joint Industry/Government/Academia Assessment of Needs and Goals"	10/97	ARD050047	TEAG11PM (Chair: S. Singhal)
9	"Software Supportability – An Overview"	1/97	AIR5121	TEAG11SW
10	"Integration of Probabilistic Methods into the Design Process"	1/97	AIR5080	TEAG11PM (Chair: E. Fox)
11	"Reliability and Safety Process Integration"	7/96	AIR5022	TEAG11
12	"Solid Rocket Booster Reliability Guidebook-Vol. II Probabilistic Design & Analysis Methods for Solid Rocket Boosters"	6/96	AIR5006/2	TEAG11
13	"Liquid Rocket Engine Reliability Certification"	4/96	ARP4900	TEAG11
14	Recommended RMS Terms and Parameters"	12/95	AIR4896	TEAG11R
15	"RMS Information Sourcebook"	11/93	ARD50046	TEAG11
16	"The FMECA Process in the Concurrent Engineering (CE) Environment"	6/93	AIR4845	TEAG11
17	"Solid Rocket Booster Reliability Guidebook"	2/91	ARD50013	TEAG11
18	"Survey Results: Computerization of Reliability, Maintainability & Supportability (RM&S) in Design"	1/90	AIR4276	TEAG11

backup

Figure 15

PRELIMINARY LIST OF PUBLICATIONS IN PROGRESS (DRAFTS MAY BE AVAILABLE FROM CHAIRPERSON)

A sample of list of publications in progress is attached here.

RMSL Division

Preliminary List of Publications in Progress (Drafts May Be Available From Chairperson)

	Title	Publ.	Product Code	Sponsor
1	"Maintainability Program Standard		JA1010	TEAG11M (Chair: W. Gregory)
2	"Basic Concepts, Models and Approximate Methods for Probabilistic Engineering Analysis"		AIR5083	TEAG11PM (Chair: D. Ghiocel)
3	"Applications of Probabilistic Methods"		AIR109	TEAG11PM (Chair: T. Torng)
4	"Legal Issues Associated with the Use of Probabilistic Design Methods"		AIR5113	TEAG11PM (Chair: A. Pickard)
5	"Reliability Testing Standard"		JA1009	TEAG11R (Chair: W. Grimes)
6	"Failure Modes, Effects, and Criticality Analysis Procedures"		J2336	TEAG11S (Chair: H. Hetrick)
7	"Supporrtability Process Standard"		J2336	TEAG11S (Chair: H. Hetrick)
8	"Guide to the Reliability Centered Maintenance (RCM) Standard		JA1012	TEAG11SL (Chair: D. Netherton)
9	"Software Supportability Program Implementation Guide"		JA1005	TEAG11SW (Chair: D. Peercy)
10	"Software Reliability – An Overview"		J2443	TEAG11SW (Chair: D. Peercy)
11	"Software Reliability Program Standard"		J2444	TEAG11SW (Chair: D. Peercy)
12	"Software Reliability Implementation Guide"		J2445	TEAG11SW (Chair: D. Peercy)
13	"Software Supportability Program Standard"		J2446	TEAG11SW (Chair: D. Peercy)
14	"Software Supportability Implementation Guide"		J2447	TEAG11SW (Chair: D. Peercy)
15	"Software Support Concept"		J2448	TEAG11SW (Chair: D. Peercy)

backup

Figure 16

WHERE ARE WE HEADED?

The Division will continue focusing on relevant RMSL and PM needs, taking advantage of web-based communication.

RMSL Division

Where Are We Headed?

- RMSL should remain the focus unless otherwise so indicated by our customers.
- Need to revitalize and reinvigorate all G-11 activities and participants based on customer needs.
- Transition to an electronically-linked network to rapidly respond to individual and organizational needs, but continue face-to-face semi-annual meetings.
- Elevate G-11 to Systems Engineering Council

Just do what's relevant & will be useful

backup

Figure 17

REVITALIZATION OF G-11

This chart outlines the Division vision and goals with focus on meeting customer needs. Our members invest hundreds and thousands of volunteer hours. We want to make sure we work only on what is relevant, needed, and will be useful to our customers such as you, the reader.

RMSL Division **Revitalization of G-11**

Vision: Be the authoritative source of RMSL information, education, and standards that the national and international leaders turn to!

Goals:

(1) Re-establish projects based on customer need only. (Initial buy-in, continuous interest, of direct use and benefit.)

(2) Link projects to participants with overlap in their day job.

(3) Communicate with senior management on what we do in conjunction with what will attract their attention.

backup

Figure 18

REVITALIZATION OF G-11 (CONTINUED)

Our goals include establishing appropriate liaisons with national and international engineering community.

RMSL Division

Revitalization of G-11 (Continued)

Goals:

(4) Establish liaisons with relevant groups. (NATO, U.K., Ministry of Defense, ISO, IEEE, NAE, -------)

(5) Broadcast relevant standards already developed by G-11.

(6) Meet at locations most likely to attract participants.

(7) Need to listen to and hold hands of new participants.

(8) Integrate RMSL workshops with RAMS

backup

Figure 19

G-11 PROBABILISTIC METHODS COMMITTEE (PMC) – VISION

Now let's talk about the G-11 Division's PM Committee. The vision was set ten years ago and we continue brainstorming, implementing, and delivering the requisite results for the benefit of the engineering community at large, with special attention to the organizations to the attending members.

G-11 Probabilistic Methods Committee (PMC)

<u>Vision</u>

To serve as the **premier** Probabilistic Methods group with **balanced**, **broad** representation in industry, government, and academia that carries with it **authoritative insight** and the ability to envision, initiate, and implement a holistic agenda for probabilistic methods that **benefits all people**.

Brainstorm, initiate & implement probabilistic projects for the benefit of all, especially member organizations

Figure 20

G-11 PROBABILISTIC METHODS COMMITTEE (PMC) – PEOPLE

This chart shows the people of the PMC organization involved in technology development, technology applications, communications, issues such as legal ones, and new initiatives.

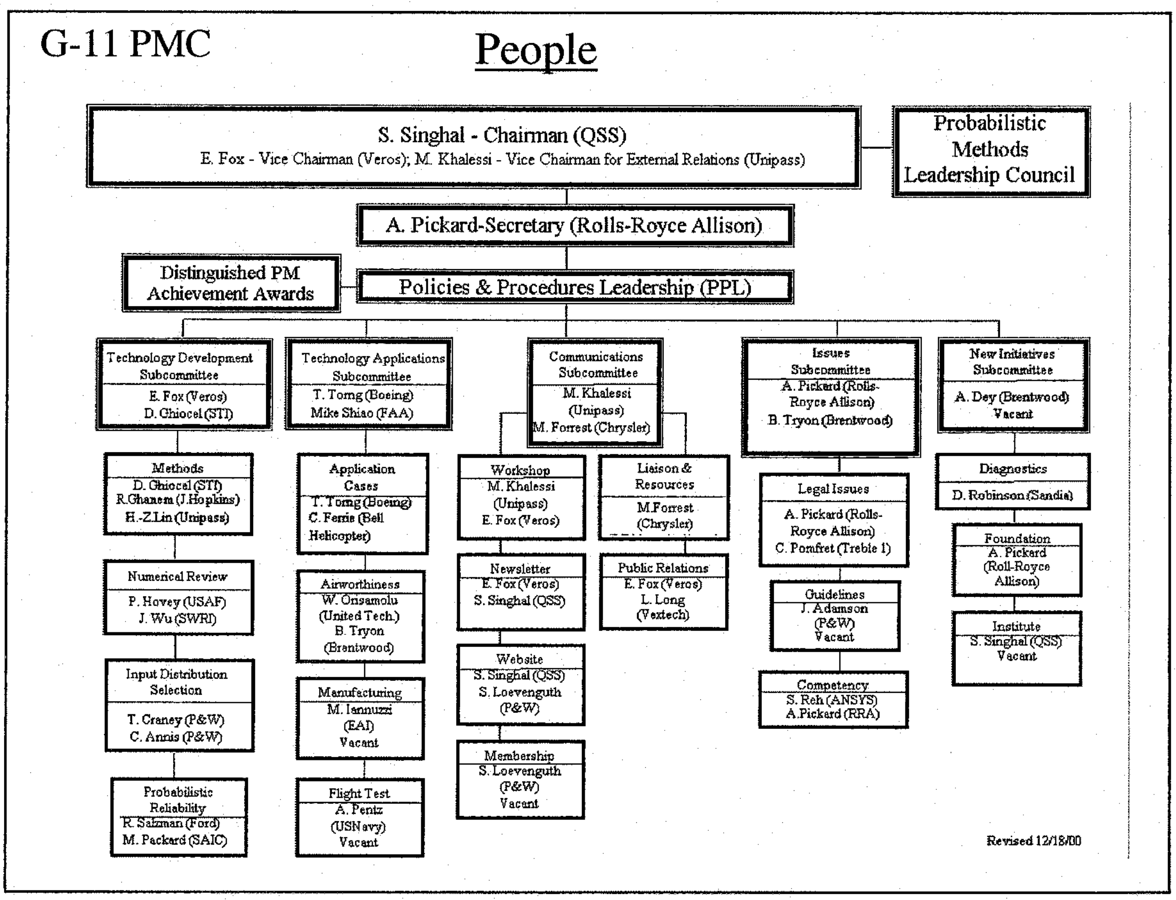


Figure 21

G-11 PROBABILISTIC METHODS COMMITTEE (PMC) – PRODUCTS

The PMC products include documents, education, training, workshops, recommendations, guidelines, and standards.

G-11 PMC

Products

- Technology Development & Applications – Compile Information
- Documents (AIR/ARD)
- Education & Training
- Recommendations to industry, government, and academia
- Standards

G-11 produces information, documents, education, training, recommendations, and standards

Figure 22

G –11 DIVISION PROJECT INFORMATION – MIAMI, FLORIDA

This page shows the information we collect for each project on the last day of each of our semi-annual meetings.

G-11 PMC

G –11 DIVISION
PROJECT INFORMATION
UPDATED AT MARCH 26-28, 2001 MEETING
MIAMI, FLORIDA

NAME OF PROJECT	
LIST OF PARTICIPANTS: **(please include e-mail address)** **This list will be published on the web page for this project. It will also serve as a special access list for the Team's Private Area located in SAE's Private Forum. This will be where draft documents reside for this project and allow easier communication among team participants.** **NOTE: INDICATE PRIMARY (P) OR SECONDARY (S)**	
AIR/ARD NUMBER AND TITLE:	
SCOPE/PURPOSE/END RESULT:	**Scope:** - - **Purpose:** - - **End Result:** ___

Please return this form to Suren Singhal or Eric Fox before leaving Meeting backup

Figure 23

G –11 DIVISION PROJECT INFORMATION – RENO, NEVADA

We further show the amount of critical information that we collect for each project. Relevance to industry is a MUST.

G-11 PMC

G –11 DIVISION
PROJECT INFORMATION
UPDATED AT OCTOBER 23-26, 2000 MEETING
RENO, NEVADA

TABLE OF CONTENTS: (If a draft is available, it will be placed on the web page for the project.)	
RELEVANCE TO INDUSTRY/GOV'T: (who is going to benefit)	
PROJECTED COMPLETION DATE:	

Please return this form to Suren Singhal or Eric Fox before leaving Meeting backup

Figure 24

G –11 DIVISION PROJECT INFORMATION – RENO, NEVADA

We conclude each project meeting with future plans for the next 6 months. Our members continue working on these projects along with their day jobs. Monthly telecons with Project, Subcommittee, Committee, and Division chairs ensure flow of information, continuity of work, and high motivation among active members.

G-11 PMC

G –11 DIVISION
PROJECT INFORMATION
UPDATED AT OCTOBER 23-26, 2000 MEETING
RENO, NEVADA

MEETING ACCOMPLISHMENTS:	
FUTURE PLANS: **(Action Items/Including Dates)**	

Please return this form to Suren Singhal or Eric Fox before leaving Meeting

backup

Figure 25

MISSION STATEMENTS FOR OUR PM COMMITTEE WEBSITE

The mission of some of our PM technology project is described on this chart.

G-11 PMC **MISSION STATEMENTS FOR OUR PM COMMITTEE WEBSITE**

Subcommittee:		**Technology**
Mission:		To develop and disseminate technical information about probabilistic Methods which can be used easily by industry, government, and academia.
1.	**Project:**	Integration of probabilistic Methods in Design
	Mission:	To develop an approach which will integrate probabilistic methodologies with design practices, procedures, and software codes currently being used.
2.	**Project:**	Computational Probabilistic Methods
	Mission:	To create a state-of the-art, nationally recognized resource document on Probabilistic methods for use by industries for advanced engineering applications and probabilistic designs.
3.	**Project:**	Applications of Probabilistic Methods
	Mission:	To capture previous experience and lessons learned in the application of probabilistic methods, and to provide examples and points-of –contact for initiating new applications.
4.	**Project:**	Probabilistic methods Case Studies
	Mission:	To provide guidelines by which probabilistic methods should be used in different types of problems.
5.	**Project:**	Integration of probabilistic methods in Manufacturing
	Mission:	To identify and describe the engineering challenges, requirements, and methods employed in manufacturing and quality control.

backup

Figure 26

TECHNICAL SUBCOMMITTEES AND PROJECTS – COMMUNICATIONS

The mission of some of our communications projects is described on this chart.

G-11 PMC

Technical Subcommittees and Projects
COMMUNICATIONS

Mission

To identify the industry need and means of rapid communication and transfer of the probabilistic technology to the industry and facilitate the adaptation of the requisite technology by the industry.

Projects

1. **Needs/Goals**
   To identify industry, government, and academia needs and goals and to ensure SAE G-11 PM Committee addresses these needs and goals. To promote PM usage in industry and government through (a) increased awareness by providing pre-eminent source of information on all aspects of PM, and (b) induced synergism by establishing communications between organizations/parties interested in PM.
2. **Workshop**
   To develop and present a workshop demonstrating practical applications of PM.
3. **Newsletter**
   To communicate G-11 and other national/international PM activities via a semi-annual newsletter.
4. **Membership**
   To expand participation of scientists, engineers, and managers in G-11 PM activities.
5. **Publications**
   To make people aware of PM technology and its potential benefits by publishing articles in engineering and non-engineering magazines.
6. **Awards**
   To recognize significant industry, government, academia PM contributions exemplifying time and cost savings, support, training, and dedication.
7. **Website**
   To create and update a website location to inform the public of G-11 PM technology and its potential benefits via an electronic environment.
8. **G-11 Liaison**

backup

Figure 27

TECHNICAL SUBCOMMITTEES AND PROJECTS – COMMUNICATIONS

The mission of some of our issues projects is described on this chart.

G-11 PMC

Subcommittee: **Issues**

Mission: To address the controversies, reluctances, litigation aspects and standards associated with the introduction of PM into design, manufacturing, certification, operation, maintenance, and retirement.

1. **Project:** Barriers to probabilistic Methods

   Mission: To address the barriers which impede the acceptance of PM in the design, manufacturing, and user communities and examine the benefits and limitations of PM so that their use can be properly understood and practiced.

2. **Project:** Probabilistic Methods Legal Issues

   Mission: To address the barriers which impede the acceptance of PM in the design, manufacturing, and user communities and examine the benefits and limitations of PM so that their use can be properly understood and practiced.

3. **Project:** Probabilistic Methods Legal Issues

   Mission: To examine the legal aspects of utilizing PM, most notably the quantification of risk/safety and the attendant ramifications.

Subcommittee: **New Initiatives**

Mission: To initiate new projects with significant potential impact on use and communication of PM technology.

backup

Figure 28

ACCOMPLISHMENTS

This chart is not to beat the drums but as a tribute to the hard and dedicated work of our members that have led to accomplishments that they can be proud of.

G-11 PMC **Accomplishments**

•In 1992, we began with 6 members with a goal of 50 in 5 years.
Nine years later today, we stand at > 100 (including non-attending ones)!

•In 1993, we began with 5 generalized long term goals.
Eight years later today, we stand at 20 (15 active) projects!

•In 1994, we began working on 1 SAE document.
Seven years later today, we have published 3, are about to publish 3 more, and are pursuing 4 more.

•In 1995, we began with the idea of PM Leadership Council.
Six years later today, we have > 30 Council members!

•In 1996, we began with an idea of a PM newsletter.
Five years later today, we have published 9 issues!

backup

Figure 29

ACCOMPLISHMENTS

Our members must continue working with the same vigor for at least a decade more, as they have in the last decade.

G-11 PMC

Accomplishments

•In 1997, we introduced 4 PM achievement awards.
Four years later today, we are preparing for the 5th award ceremony!

•In 1997, PMLC recommended we conduct PM Workshops.
We presented PM Workshops in 1997 & 1998!

•In 1999 and 2000, we focused on & demonstrated stable growth in the PM attendees & enhanced our linkage with industries.

•In 2001, we are beginning with more bold ideas!!

We are influencing our organizations' competitiveness!

With your dedication, anything is possible!!

backup

Figure 30

STATUS OF DOCUMENTS

A status of some of our current documents is delineated here.

G-11 PMC **Status of Documents**

Category	Title	%Complete	Estimated Completion Date	SAE Report #
Technology	Probabilistic Engineering Methods, Volume I	99%	10/1	AIR 5083
	Probabilistic Engineering Methods, Volume II	75%	1st draft by 10/01	Not Yet Assigned
	Numerical Review	75%	1st draft by 10/01	AIR 5110
	Input Distribution Selection	5%	Outline by 10/01	Not Yet Assigned
	Probabilistic Reliability	20%	1st draft by 10/01	Not Yet Assigned
Applications	Application Cases	80% (Volume 1)	Final by 10/01	AIR 5109
	Airworthieness	70%	1st draft by 10/01	Not Yet Assigned
	Manufacturing	40%	In Progress 3/03	Not Yet Assigned
Issues	Legal Issues	99%	Approved	AIR 5113
	Guidelines		Discussion Phase 10/02	AIR 5115
	Minimum Competency	40%	10/1	Not Yet Assigned
	Diagnostics		Just Beginning 10/03	Not Yet Assigned
	Flight Test Cost Reduction	5%	Outline by 10/01	Not Yet Assigned

Figure 31

FUTURE PLANS

The future of the SAE G-11 PMC is to continue the path it embarked upon about ten years ago, i.e., keep working until PM becomes a routine practice.

G-11 PMC

Future Plans

G-11 PMC as an internationally recognized premier source for:

- PM Information
- PM Experts
- PM Applications
- PM Training

Keep working until PM becomes a routine practice!

Figure 32

PROBABILISTIC METHODS LEADERSHIP COUNCIL

This chart describes the charter and focus of the PMLC, an organization that took birth about 5 years ago to serve as the senior advisory council to the SAE G-11 PMC and to encourage the implementation of PM in the industry. The Council is comprised of senior executives from industry, government, and academia.

Probabilistic Methods Leadership Council

- Charter – High-Level Advisory Group
- Members – Senior Executives
- Current Focus – Risk Assessment & Probabilistic Design Practice
- On-Going Projects – Recommend minimum PM competency to engineering accreditation board

Leadership Council has made a difference in accomplishing the G-11 PMC vision.

Figure 33

AIAA ACTIVITIES

This chart lists the two AIAA activities. The PM subcommittee of the Structures TC that started about ten years ago is now focused on service life design and reliability assessment. About three years ago, the Non-deterministic Approach (NDA) Forum was established to serve the growing need of the engineering community.

AIAA Activities

- Technical Subcommittee on Service Life Design & Reliability Assessment & the NDA Forum
- Working Technical Group – Nondeterministic Approaches (NDA)

AIAA Structures TC web site:

http://jafar.ncsa.uiuc.edu/aiaa/organization/TechSub/reliability.html

Figure 34

TECHNICAL SUBCOMMITTEE ON SERVICE LIFE DESIGN & RELIABILITY ASSESSMENT

This chart outlines the AIAA activities in the area of PM and NDA, mostly focused on panel discussions and paper presentations, unlike the SAE G-11 activities, which are three days of, focused interaction on PM with your peers.

AIAA

Technical Subcommittee on Service Life Design & Reliability Assessment

- Initiated as Probabilistic Methods (PM) Subcommittee of the Structures TC in 1993
- Initiated & successfully implemented focused sessions on PM papers at the annual SDM Conference
- Initiated & have organized a panel discussion at the annual SDM Conference.
- Approved by AIAA as NDA Forum

The aerospace professional engineering community has pulled together to make AIAA activities a success

Figure 35

WORKING TECHNICAL GROUP – NONDETERMINISTIC APPROACHES (NDA)

This chart describes the NDA working technical group.

AIAA

Working Technical Group –
Nondeterministic Approaches (NDA)

- An electronic committee dedicated to furthering the implementation of nondererministic approaches in the engineering community
- Conducted a joint industry/government/academia workshop for nation-wide recommendations on the use of nondeterministic approaches.

A dedicated group of members continue to encourage the use of nondeterministic approach

Figure 36

OTHER NON-PROFIT PROFESSIONAL ACTIVITIES

This chart gives the address of a nonprofit website with a focus on nontraditional approaches. The web site will be open soon. NDA and PM will be a major part of this web site.

Other Non-Profit Professional Activities

A web-based professional community & resource for non-traditional approaches:

WWW.NTACENTER.COM

- Web site under construction
- First segment with focus on PM & NDA accessible in August, 2001

A central one-step web-based resource for non-traditional approaches for America tomorrow!

Figure 37

CONCLUSIONS

In conclusion, there is evidence out there that the probabilistic approaches will provide an order-of-magnitude savings, which can be measured. The SAE G-11 PMC provides a forum to bring the people and technology together. There are publications dealing with PM technology, applications, and communications issues that may be useful for any organization engaged in understanding and implementing probabilistic approach.

Conclusions

- Payoff from interdisciplinary probabilistic engineering will be orders of magnitude of investment.

- SAE G-11 PMC provides a forum:
  - to learn from each other
  - to compile & disseminate relevant information

SAE is fulfilling the current PM need

Figure 38

RECOMMENDATIONS

On behalf of the SAE G-11 PM Committee, recommendations to adopt the PM technology are to first sensitize our engineers to start thinking probabilistically, followed by education and access to relevant tools. We must first realize the PM benefits on a small project, before going full scale and realizing the full PM potential.

Recommendations

- Sensitize & Educate yourself
- Find the right tools
- Start with applying PM to the right prototype
- Realize full potential of PM

PM – A ROUTINE PRACTICE!

Figure 39

YOUR ACTION PACK

For those interested in joining or just learning more about the SAE G-11 PM activities, you may propose a project of your interest for our consideration or submit a PM application for publication in our resource documents. The bottom line is – MANAGE UNCERTAINTIES OR RISK BEING MANAGED BY THE UNCERTAINTIES - THE CHOICE IS YOURS!!

Your Action Pack

(1) **Get involved in G-11** - Announcement for the next G-11 PMC meeting

(2) **Propose your project** – New Project executive Summary Form

(3) **Submit a PM application for publication** – PM Application Summary Sheet

(4) **Inform your colleagues** - Suggestion for potential new members

Manage Uncertainties OR

Risk Being Managed by Them!

Figure 40

ACTION (1) GET INVOLVED IN G-11
ANNOUNCEMENT FOR THE NEXT G-11 PMC MEETING

This chart includes a brief description of projects to be discussed at the next G-11 meeting.

Action (1) Get Involved in G-11
Announcement for the next G-11 PMC Meeting

The Fall 2001 Meeting of the SAE G-11 Probabilistic Methods Committee will be held in Monterey, California during October 1-3, 2001.

<u>The three-day meeting will be focused on technical discussions among your peers from industry, government, and academia.</u>

The topics to be discussed include:

(1) **Probabilistic Engineering Methods** – What are the various probabilistic methods, how are they alike and/or different, where are they applicable, and how can you use them in real-life?

Relevance to Industry & Government – Details and references on various probabilistic methods and recommendations on which methods can be used for what real-life problem.

(2) **Numerical Review**- Several typical engineering problems are being solved using different probabilistic simulation codes. The discussion includes: what problems, what results by different methods, and how can industry use which code for what problem.

Relevance to Industry & Government – Case studies of typical problems encountering uncertainties, results of solutions to these problems run by different codes, and recommendations on which code is applicable where.

(3) **Input Distribution Selection** – What distribution to select when there is little or no data?

Relevance to Industry & Government – Too often, we get bogged down thinking we need a lot of data before we can quantify uncertainties. Not True. There are ways to do credible probabilistic analysis with little data.

(4) **Application Cases** – We are compiling the applications of probabilistic analysis demonstrating time & cost savings by various organizations.

Relevance to Industry & Government – Too often, we say, "Show Me the Proof of the Pudding". With help from many contributors, we hope to produce such a document. Problem is – not too many people are coming forward due to proprietary nature. So, we are asking to document only minimum information including problem description, what method used, did it result in any savings, and how much?

(5) **Airworthiness** – How to use probabilistic methods for airworthiness – a project proposed by a PMLC Member.

Relevance to Industry & Government – Airworthiness is a key issue for the aerospace community. There are uncertainties associated with it. By learning how to assess the effects of these uncertainties, we hope to be able to help industry produce airworthy vehicles which are more efficient and cost effective at the same time.

Figure 41

ACTION (1) GET INVOLVED IN G-11
ANNOUNCEMENT FOR THE NEXT G-11 PMC MEETING

This chart continues the brief discussion of the projects to be discussed at the next G-11 PM meeting.

(6) **Manufacturing** – This project started with plans for integrating probabilistic methods in the manufacturing process but is currently focused on dimensional tolerancing during the manufacturing process.
Relevance to Industry & Government – Tolerancing during the manufacturing process is a key issue that governs warranty, cost, failure rate, etc. With this project, we hope to provide guidance on tolerancing.

(7) **Legal Issues** – We are looking at legal precedence and what issues may arise when you use probabilistic methods.
Relevance to Industry & Government – There is the widespread belief that when things are designed using deterministic approach, they are designed correctly. And that if you use probabilistic approach, you designed it to fail (one in so many times). Sure, it invites public scrutiny. The fact is, it is the probabilistic approach that accounts for real-life uncertainties allowing us to design correctly.

<u>A paper was published in an AIAA Conference with an eye-opening conclusion – if an organization does not use probabilistic methods, tools for which are now available, then that organization could be find negligent for not using such tools.</u>

(8) **Standards** – What standards need to be set by whom, when, etc.?
Relevance to Industry & Government – Much discussion is taking place in consultation with FAA, industry, and others on how to go by start setting a pilot standard for certification by probabilistic methods, eventually leading to full standards for analysis, design, manufacturing, testing, certifications, maintenance, operations, and retirement.

(9) **Competency** – What is the minimum competency in probabilistic methods that our engineers should have before graduating from college? This project was proposed by SAE PMLC.
Relevance to Industry & Government – We have initiated contact with ABET and are brainstorming as to what should our engineering colleges teach, both on the undergraduate and the graduate level so that our industry and government don't have to spend a lot of money training engineers in how to quantify uncertainties.

(10) **Diagnostics** – How to incorporate probabilistic methods into diagnostics?
Relevance to Industry & Government – Knowing how to account for uncertainties in diagnostics, can lead to significant cost savings and can result in reducing failures.

(11) **Probabilistic Reliability** – How to compute reliability by quantifying uncertainties?
Relevance to Industry & Government – Correct reliability computations both at the component and system level are needed so one can design an item based on its expected usage and life span.

(12) **Flight Test Cost Reduction** – How can one reduce the high cost and time of flight testing? We will look at the whole picture including analysis, ground testing, and in-flight testing? This project was inspired by the Boeing President for Phantom Works, Mr. Swain.
Relevance to Industry & Government – cost savings and faster time to market!!

There are other ongoing operational projects. If you can make a good case, we will consider a new project that can help our industry and government. For further information, contact:

Meeting Details: Kerry Tielsch (ktielsch@sae.org)
Technical: Suren Singhal (ssinghal@grc.nasa.gov)

Figure 42

ACTION (2) – PROPOSE YOUR PROJECT
NEW PROJECT EXECUTIVE SUMMARY FORM

This chart is the new project executive summary form. You are welcome to complete one for the project of your interest and submit it to SAE.

Action (2) – Propose your project
New Project Executive Summary Form

Title: ____________________

Submission Date: ____________ **Revision:** ____________

Project Leader: ____________ **Alternate:** ____________

(Address) ____________ ____________

(Phone/Fax) ____________ ____________

(E-mail) ____________ ____________

Background: ____________________

Objective(s): ____________________

Scope: ____________________

Benefit to Industry/
Government/Academia: ____________________

Relation to Other AIR's: ____________________

Target Dates: **Outline -** ____________
First Draft - ____________
Expected Completion Date - ____________

When completed, please submit to your committee chairperson.

Figure 43

ACTION (3) – SUBMIT A PM APPLICATION FOR PUBLICATION
PROBABILISTIC METHODS APPLICATION SUMMARY SHEET

You may use this form to submit an application of probabilistic methods for publication in an SAE document

Action (3) – Submit a PM application for publication

Probabilistic Methods Application Summary Sheet

1. **Application No:** (Do not answer this question)
2. **Type of Industry:**
3. **Project Title:**
4. **Reason for Using Probabilistic Approach:**
5. **Probabilistic Method Used:**
6. **Rationale for Selection of the Type of Probabilistic Analysis Used for This Application:**
7. **Probabilistic Analysis Results Summary and Benefits:**
8. **Describe Whether or Not the Results Were Verified (Analytically, or by Test):**
9. **Potential Application of This Analysis to Other Industries:**
10. **Cost Versus Benefits Analysis:**
11. **Referenced Technical Report or Paper:**

Please submit to Suren Singhal at:
ssinghal@qssgess.com

Figure 44

ACTION (4) – INFORM YOUR COLLEAGUES
SUGGESTIONS FOR POTENTIAL NEW MEMBERS – PLEASE PRINT

This page is for sharing with those interested in joining the SAE G-11 PM Committee. Hopefully, you may benefit from the work of professional engineering societies. Together, we can make a difference.

Action (4) – Inform your colleagues
Suggestions for Potential New Members – Please Print

Name:	Last:	First:
Company:		
Email:		
Phone Number:		
Fax#:		
Address:		
Name:	Last	First:
Company:		
Email:		
Phone Number:		
Fax#:		
Address:		
Name:	Last:	First:
Company:		
Email:		
Phone Number:		
Fax#:		
Address:		

SUBMITTED BY:__________ Phone#:__________

Email:__________

Figure 45

Probabilistic Approaches for Evaluating Space Shuttle Risks

William Vesely
Space Shuttle PRA Coordinator

Probabilistic Approaches for Evaluating Space Shuttle Risks

Bill Vesely
Space Shuttle PRA Coordinator

May 31, 2001

Figure 1

Objectives of the Space Shuttle PRA

- Evaluate Mission Risks
- Evaluate Uncertainties and Sensitivities
- Prioritize Contributors
- Evaluate Upgrades
- Track Risks
- Provide Decision Tools

Figure 2

Space Shuttle PRA Significance

- Largest Space Shuttle PRA Effort to Date
- Direct Participation of the NASA Centers
- Recognized by the Space Shuttle Program
- Model Integration Across JSC, MSFC, KSC
- NASA Headquarters Support and Oversight
- NASA Computer Code and Models

Figure 3

Space Shuttle PRA Participants

- JSC, MSFC, and KSC
- NASA Headquarters
- Prime Contractors-USA, Boeing, Rocketdyne, Morton-Thiokol, Pratt-Whitney, Lockheed-Martin
- Support Contractors- SAIC, HEI
- Supporting Consultants

Figure 4

Space Shuttle Elements

- Space Shuttle Main Engines (SSMEs)
- Solid Rocket Boosters (SRBs)
- External Tank (ET)
- Redesigned Solid Rocket Motors (RSRMs)
- Advanced High Pressure Pumps (ATHPPs)
- Orbiter

Figure 5

Types of Losses

- Loss of Crew and Vehicle
- Processing Incurred Losses
- Mission Aborts
- Mission Partial Failures
- Economic Losses

Figure 6

Risk Contributors

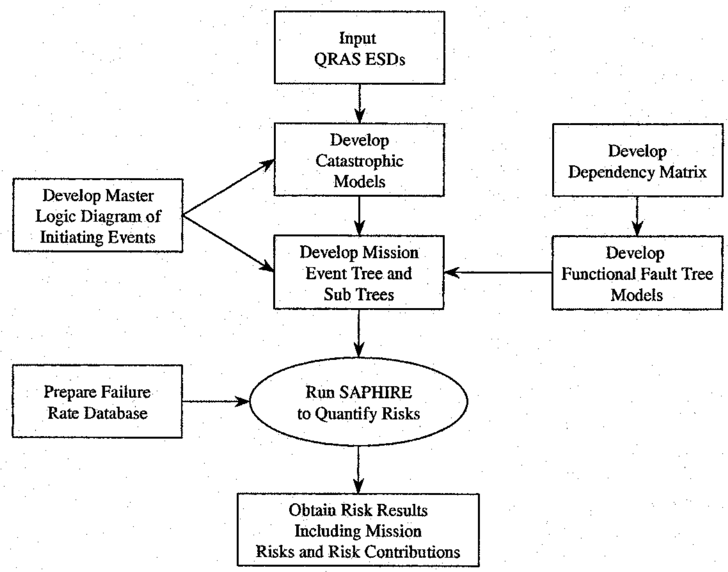
- Hardware Failures
- Fires and Explosions
- Human Performance
- Processing Effectiveness
- Cracks and Leaks
- Aging Degradations

Figure 7

Program Approach

- Develop Risk Framework
- Identify Risk Elements to be Included
- Establish System Engineering Interfaces
- Develop Risk Models
- Assemble Data
- Quantify Risks and Uncertainties
- Support Applications

Figure 8



Space Shuttle PRA Flow Diagram

Figure 9

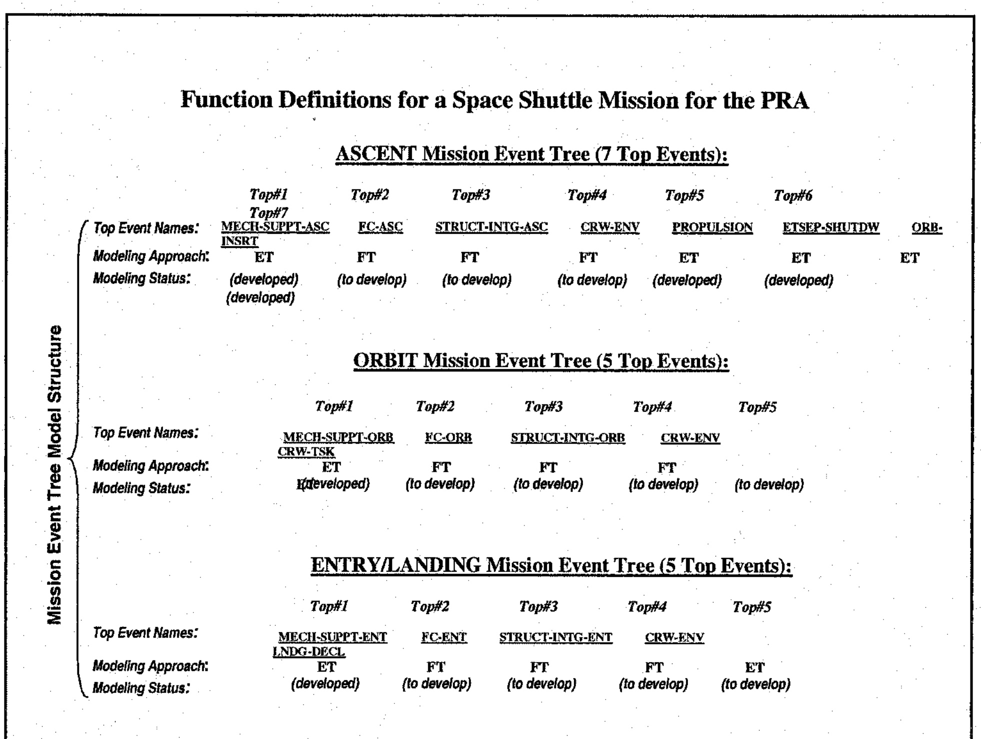
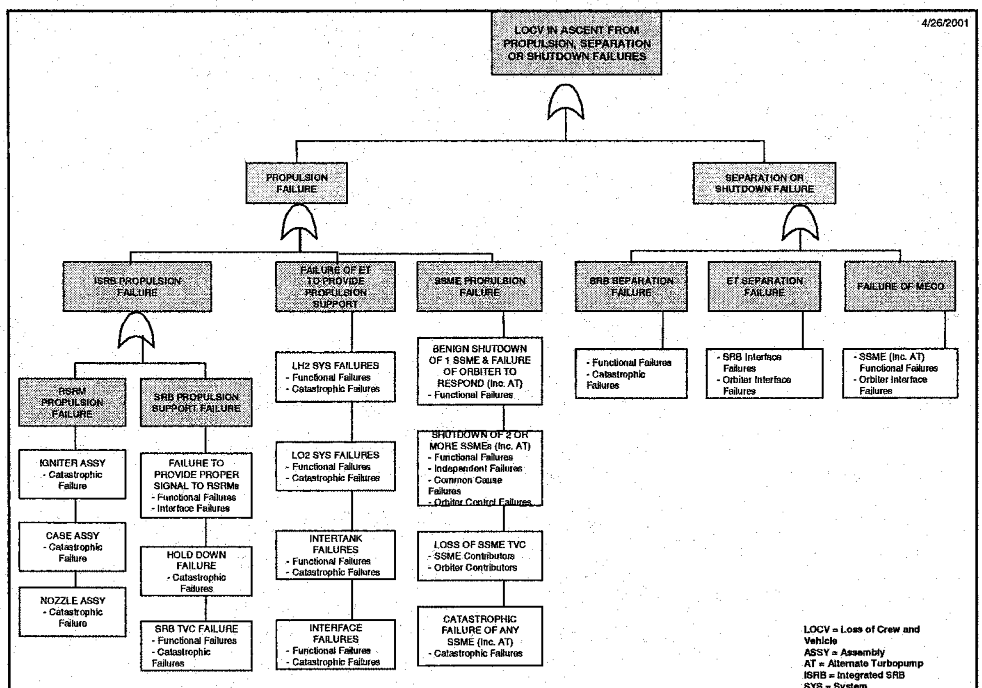


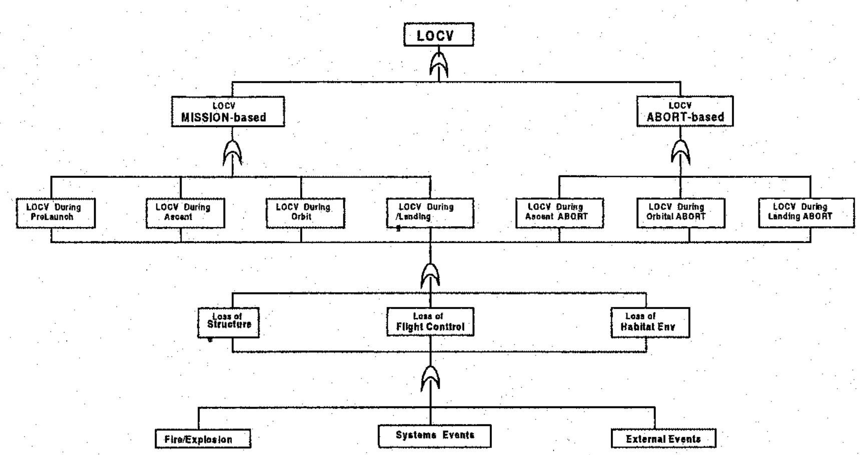
Figure 10



EXAMPLE MASTER TREE FOR FUNCTIONAL AND CATASTROPHIC FAILURES TO BE MODELED

Figure 11

Top Levels of a Master Logic Diagram (MLD) For a Space Shuttle PRA



Top Levels in the Logic Diagram for Hazards to be Evaluated

Figure 12

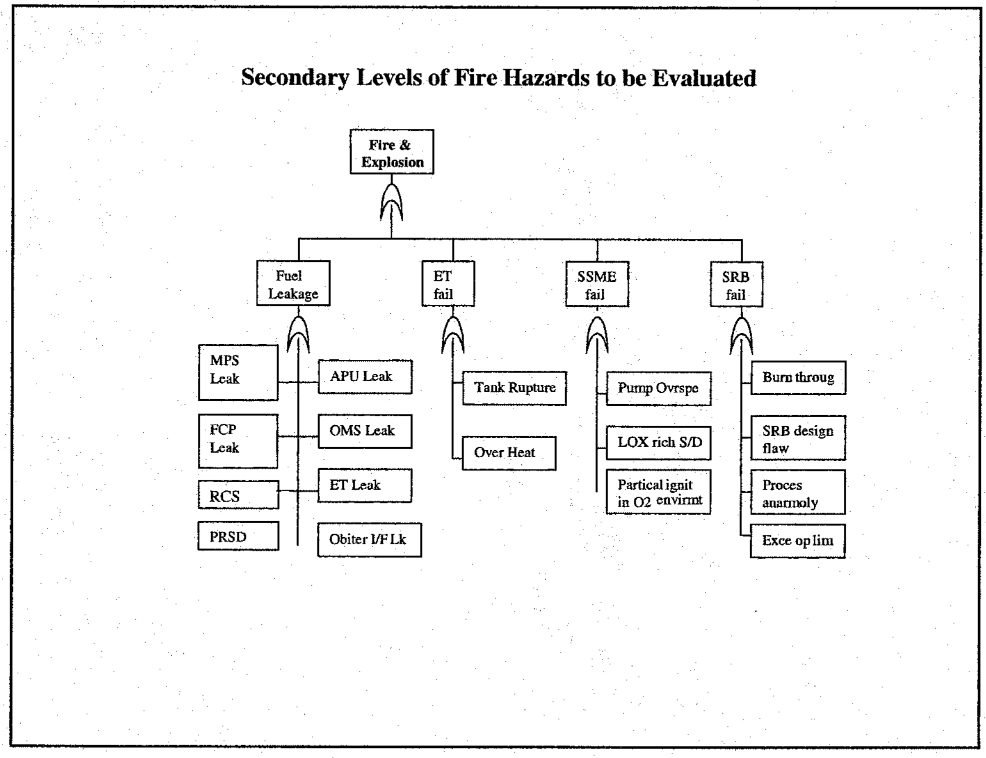
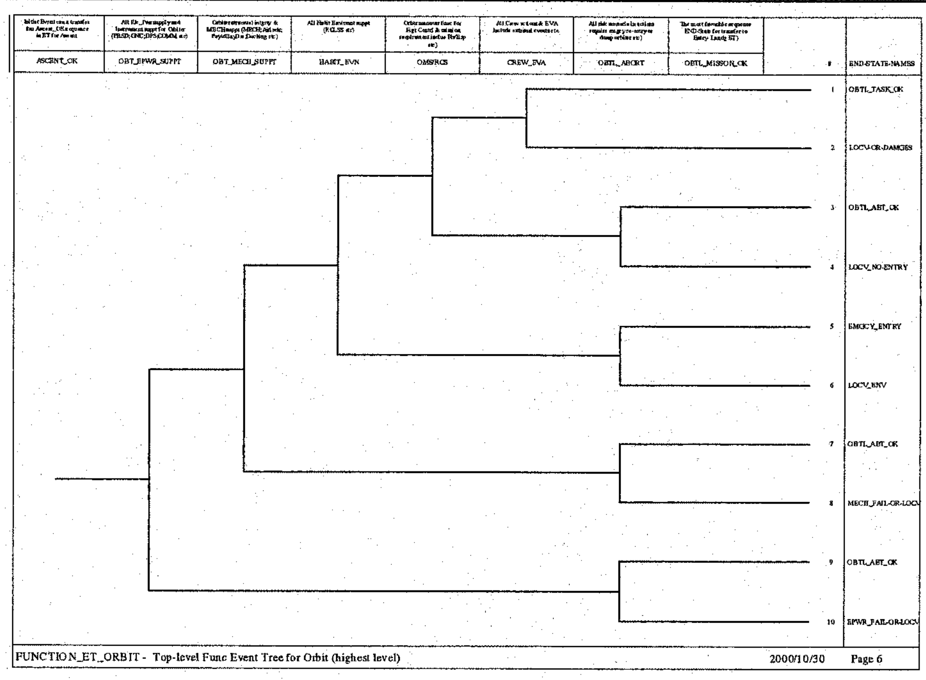


Figure 13

Probabilistic Approaches

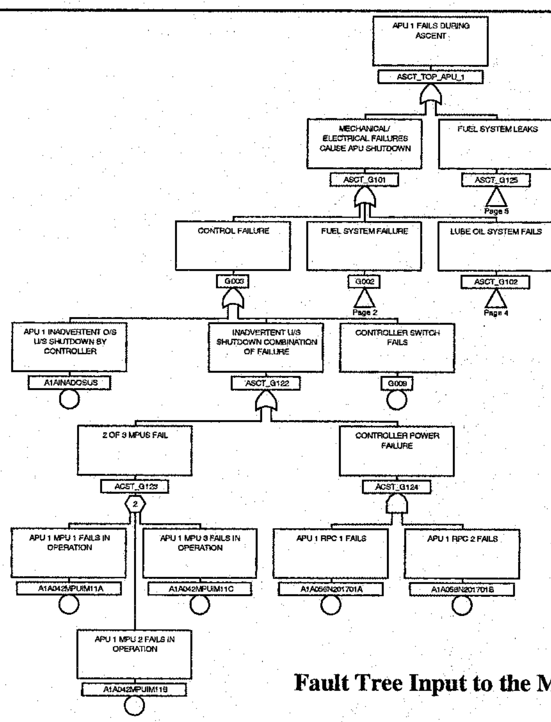
- Reliability Models
- Phenomenological Models
- Dependency Modeling
- Probability Networks
- Bayesian Probability and Statistics
- Sensitivity Studies and Designs
- Decision Theory Applications

Figure 14



Event Tree for Sequencing Function Requirements in a Space Shuttle Mission

Figure 15



Fault Tree Input to the Mission Event Tree

Figure 16

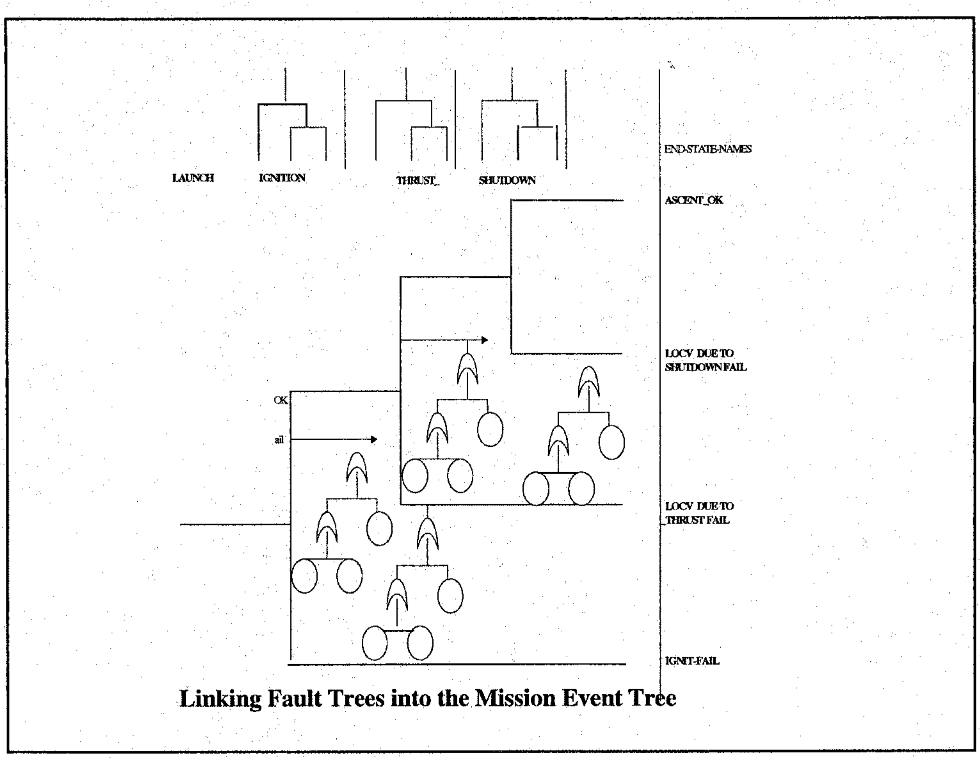


Figure 17

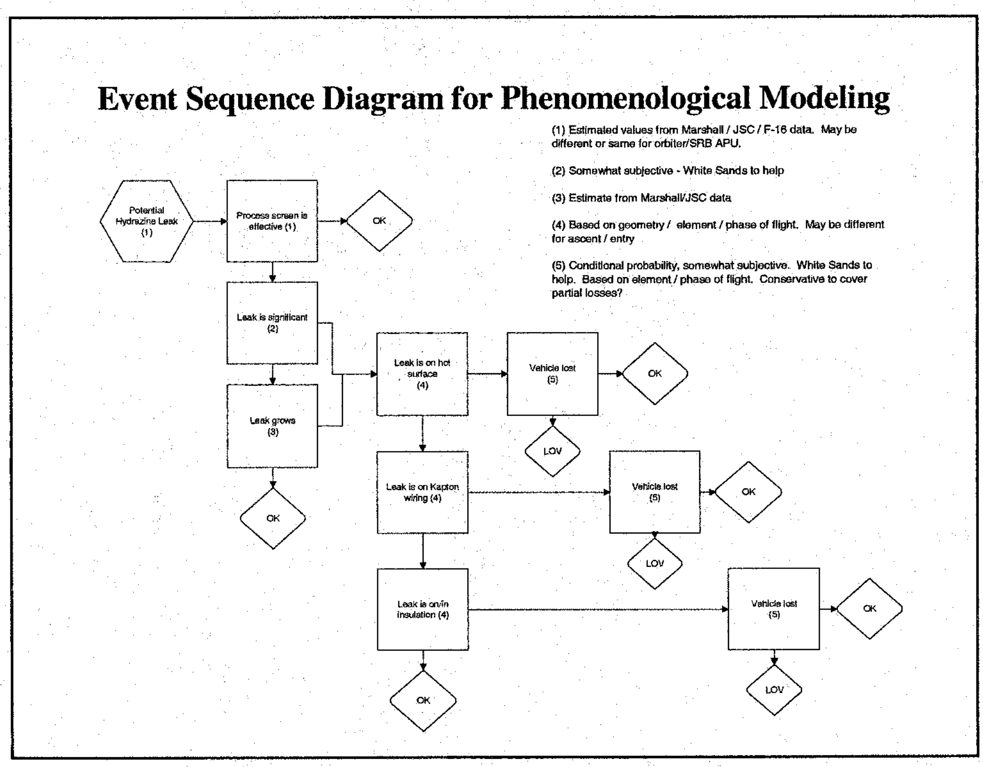
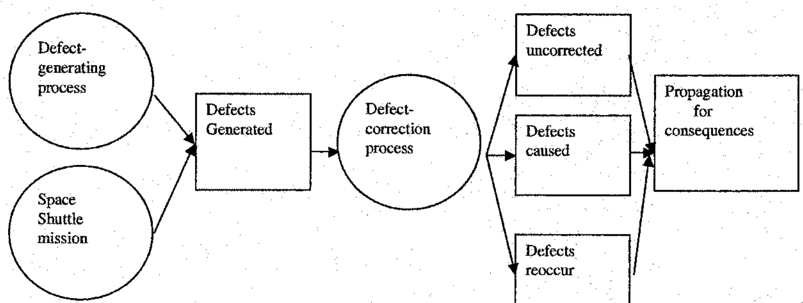
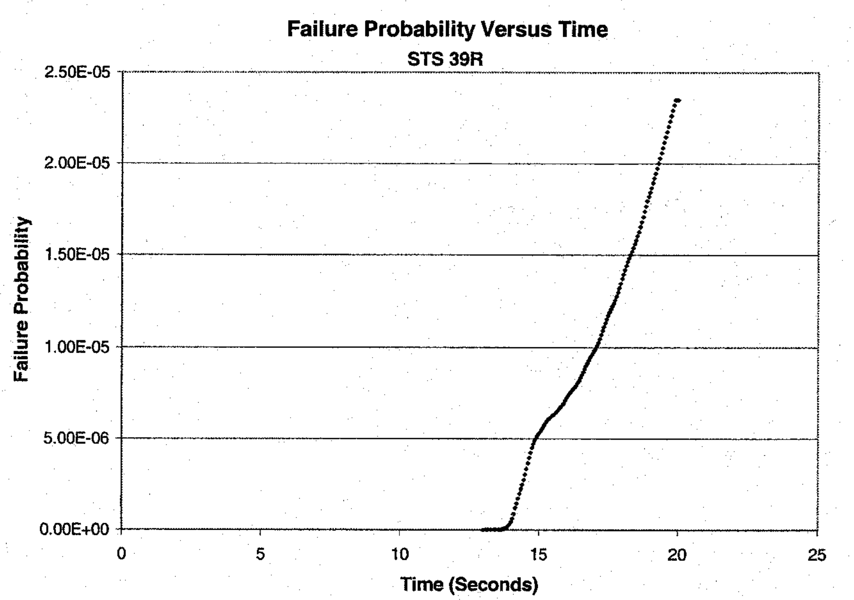


Figure 18



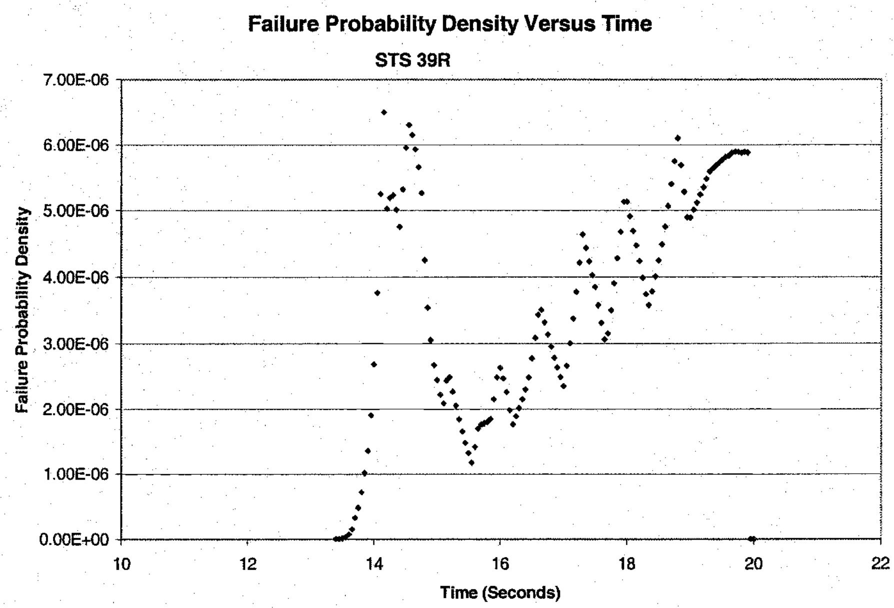
Probability Network for Modeling Process Contributions

Figure 19



FAILURE PROBABILITY PROFILE FOR A TIRE FAILURE IN AN ORBITER LANDING

Figure 20



TIRE FAILURE PROBABILITY DENSITY PROFILE IN AN ORBITER LANDING

Figure 21

Modeling Objectives

- Consistency Across Diverse Elements
- Modularized Risk Models
- Prioritization of Hardware, Humans, and Processes
- Thorough Treatment of Uncertainties and Sensitivities
- Defensible Results and Conclusions
- Effective Presentations

Figure 22

Program Status

- Modeling Guidelines Issued
- Risk Framework Model Developed
- Risk Elements Defined
- First Stage Models Being Completed
- Computer Models Being Constructed
- Initial Results End of FY01
- Final Results End of FY02
- Future Extensions Being Planned

Figure 23

REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 2001	Conference Publication

4. TITLE AND SUBTITLE
Nondeterministic Approaches and Their Potential for Future Aerospace Systems

5. FUNDING NUMBERS
WU 282-10-11

6. AUTHOR(S)
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